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THESIS

COMBAT SIMULATION OF INDIVIDUAL SOLDIER SEARCH IN URBAN TERRAIN

by

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June 2009

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13. ABSTRACT (maximum 200 words)

This thesis investigates the visual search process and the effect of contextual information on the search process in an urban combat environment. High resolution combat simulation models implement a parallel sweeping or "windshield wiper" search process that is not representative of human search behavior. Furthermore, combat models do not account for additional situational awareness in the form of contextual information. This thesis proposes a Discrete Myopic Search model, which provides a statistical model based on human performance data. This model prioritizes search effort where humans believe that targets are most likely to occur. Nineteen volunteers searched 16 static urban scenes with zero to five targets. These data formed the probabilities that a target is located in each cell in each discretized scene. The Discrete Myopic Search model chooses the cell with the highest probability for each discrete look. Hypothesis testing on experimental data revealed a nearly 20% increase in search performance of the Discrete Myopic Search model over the windshield wiper model. Further investigation revealed a significant change in search behavior and detection performance based on the addition of contextual information. This research shows that combat models should prioritize search patterns and account for added situational awareness.

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COMBAT SIMULATION OF INDIVIDUAL SOLDIER SEARCH IN URBAN TERRAIN

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ABSTRACT

This thesis investigates the visual search process and the effect of contextual information on the search process in an urban combat environment. High resolution combat simulation models implement a parallel sweeping or “windshield wiper” search process that is not representative of human search behavior. Furthermore, combat models do not account for additional situational awareness in the form of contextual information. This thesis proposes a Discrete Myopic Search model, which provides a statistical model based on human performance data. This model prioritizes search effort where participants believe that targets are most likely to occur. Nineteen volunteers searched 16 static urban scenes with zero to five targets. These data formed the probabilities that a target is located in each cell in each discretized scene. The Discrete Myopic Search model chooses the cell with the highest probability for each discrete look. Hypothesis testing on experimental data revealed a nearly 20% increase in search performance of the Discrete Myopic Search model over the windshield wiper model. Further investigation revealed a significant change in search behavior and detection performance based on the addition of contextual information. This research shows that combat models should prioritize search patterns and account for added situational awareness.

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EXECUTIVE SUMMARY

Combat simulation models are widely used for both training and developing courses of action. These reasons show the importance of valid output of such models. Unfortunately, these models do not implement a visual search process that is representative of a human soldier. The order in which a simulation model detects targets is not consistent with the order in which a human detects targets. If a human does not engage the most dangerous target first, he will most likely become a casualty. If a brigade or division of soldiers does not engage targets in an appropriate manner, the battle may be lost. Even a small probability of error can quickly change the outcome of a battle when the number of soldiers is very large. This thesis shows the flaw in the search pattern used by current simulation models and proposes a Discrete Myopic Search model. The presented model is validated using experiment data from observation of human subjects and contrasted with the currently implemented model using a population proportion hypothesis test. The analysis highlights a nearly 20% improvement in the correct prediction of the target detection order when utilizing the Discrete Myopic Search model. Such an improvement will undoubtedly change the mind of decision makers for certain courses of action.

Further, simulation models currently do not account for additional situational awareness of individual entities in the form of contextual information. This thesis shows that such information not only changes the search behavior of human participants, but also affects detection performance. Sharing information among soldiers is crucial in an urban combat environment. Simulation models should also reflect this role of information sharing among individual searching entities.

Current U.S. Army doctrine prescribes a thorough search technique for operations in rural terrain. The doctrine explains that urban terrain is more complex, but stops short of prescribing a search technique. This thesis uses experiment data to show that typical rural search techniques are not sufficient for urban terrain. It goes on to recommend language for further investigation and consideration in future doctrinal manuals regarding search in an urban environment.

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I. INTRODUCTION

A. MOTIVATION

Imagine a young soldier providing security over his sector in the streets of an urban combat zone. Three targets present themselves simultaneously, each of them clearly an enemy combatant. The first target is approximately 250 meters to the soldier's eleven o'clock. This target is oriented in a direction which poses no immediate threat to the soldier. The second target is approximately 200 meters to the soldier's front and clearly has not yet observed the soldier. The last target is 25 meters to the soldier's two o'clock and is raising his weapon to engage the soldier. Unfortunately, the soldier is programmed to implement a predetermined search pattern, which sweeps from left to right. Before he can engage the target which is the highest threat, he must first adjudicate the two very low threat targets. The third target engages and kills the soldier before the soldier ever acquires the target.

Now imagine the same soldier in a similarly hostile urban situation. This time there is one target 200 meters to the front on a rooftop preparing the engage the soldier. The soldier implements a search pattern in which he considers 100-meter strips of terrain from left to right and right to left from near to far overlapping strips on each pass. The terrain to his immediate front consists of a road and buildings on either side with closed doors and windows, none of which pose any immediate threat. Just as in the first case, the target engages and kills the soldier before the soldier can acquire the target.

The first situation describes the search pattern implemented by high resolution combat simulation models. The second situation describes a search pattern prescribed by several U.S. Army field manuals. In both cases the soldier loses the fight. Urban terrain contains vast amounts of clutter, provides exceedingly more occlusions than rural terrain, and requires a more deliberate search technique. This thesis proposes an urban search technique based on the likelihood of a target's presence at any point in a given field of view. This technique prioritizes the order of a searcher's gaze pattern based on the probability that a target is present.

B. BACKGROUND

At the most basic level of modern tactical ground combat, an individual combatant seeks to destroy his enemy in close battle. Fundamental to a combatant's ability to destroy his enemy is the search and target acquisition process. A combatant must first search for a stimulus, identify any discovered stimulus as an enemy combatant, determine whether or not the situation satisfies the Rules of Engagement, and ultimately engage the target. This research investigates the visual search patterns—the cornerstone of the search and target acquisition process—of an individual, dismounted soldier in an urban environment.

This study uses eye tracking data to investigate how an individual with military training searches a static scene to identify hostile targets. The data include *x* and *y* pixel coordinates of the gaze on a computer screen of each individual participant at a rate of 60 data points per second. In addition, mouse click data indicate whether the participant correctly identifies a target or if he falsely identifies a stimulus that is not a target. A miss results when the participant fails to identify a target. These data form the basis for the measures of effectiveness with which this thesis analyzes and compares current and proposed search models.

More precisely, this research focuses on the fixation data derived from the eye tracking information and the probabilities of detection derived from the mouse click data to formulate a Myopic Allocation of Search Effort model. This model determines the optimal allocation of search effort for each of a finite number of discrete looks at a partitioned image. This thesis seeks to improve upon the search process, that is, the order of target detections, rather than the detection statistics themselves; detection probabilities derived from experimental data remain fixed throughout the model comparison.

1. Search and Target Acquisition

Search is defined herein as the process of viewing a search field to locate a target. Target acquisition is all processes needed to locate a target and discriminate it to a desired level. These processes include detection, classification, recognition, and identification (Vaughan, 2006).

Detection is the determination that an object exists such that it is distinct from its surroundings. Classification is a decision whether or not the object belongs to a set of targets or non-targets. Recognition is a process which determines the specific functional category to which the object belongs. Identification is the most detailed level of discrimination and leads to the decision of whether or not a target is hostile (Vaughan, 2006).

The Search and Target Acquisition Process is essential to this research and critical to a successful combat operation. Timely and accurate implementation of this process by an individual entity in a combat simulation model or an individual soldier in the streets of a hostile urban environment can prove the difference between mission success or failure.

2. Search in Current Combat Models

Current high resolution combat simulation models such as OneSAF and COMBATXXI implement a specific, discrete search process. This process begins by dividing a field of regard (FOR) into discrete, adjacent, and non-overlapping fields of view (Harrington, 2009). The models then apply acquisition methodology, described below, to each FOV in a "windshield wiper" pattern (TRAC WSMR, 2008). Figure 1 displays a flow chart of the FOV search. Note that this search is for only one FOV in the FOR. Once this search is complete, the model moves to the next FOV.

The ACQUIRE model is the Army's standard implementation of the search and target acquisition process in current combat simulations (Mazz, 1998). The model determines the probability of acquiring a target based on inputs describing the target, sensor, and environment (Mazz, 1998). Combat models implement the ACQUIRE model within the FOV search methodology in Figure 1. It is pertinent to note that the ACQUIRE model was originally developed to model night vision devices and not human vision (TRAC WSMR, 2008).

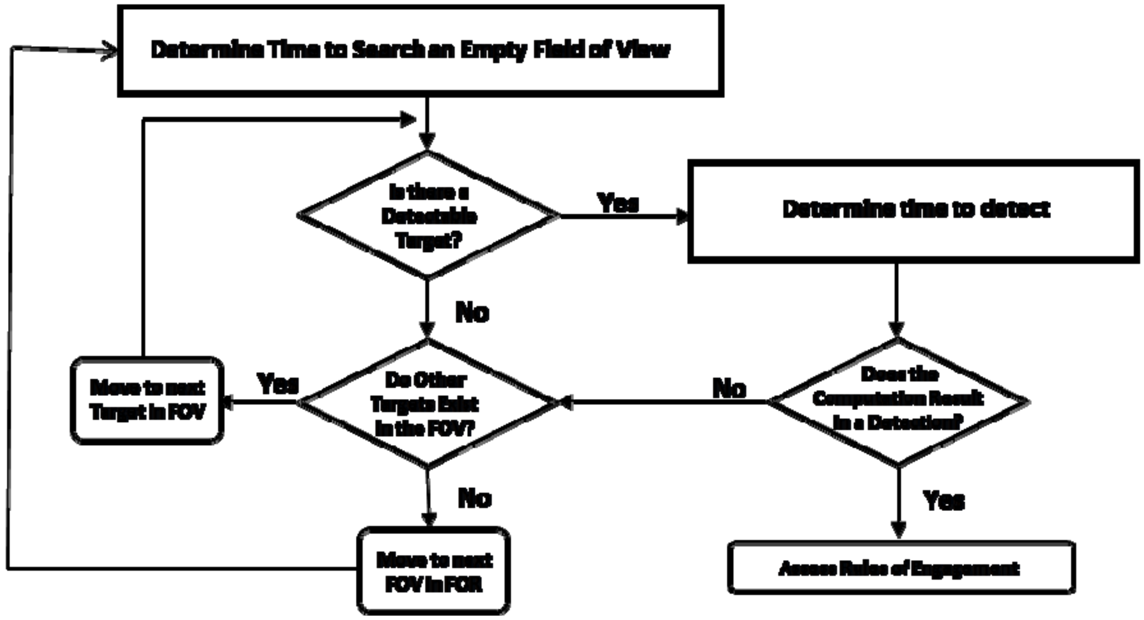

Figure 1. FOV search methodology for OneSAF and COMBATXXI shows the progression of decisions which determine whether a target detection occurs and when to move to the next FOV within the specified FOR. This chart is an abstraction of the actual search methodology, which excludes critical computations required for each step. [After U.S. Army Materiel Systems Analysis Activity, 2007]

This thesis does not address detection performance nor is it concerned with a single FOV search. This research disputes the FOR search in an urban environment. Jones and Lai conducted an FOR search experiment in which a 4200 pixel by 900 pixel FOR was divided into 14 uniform sized 600 pixel by 450 pixel FOVs. They designed the experiment to better understand the search and target acquisition process in an urban environment for a given FOR (Jones & Lai, 2007). A similar division of the images in the experiment described in Chapter II of this thesis would result in nine FOVs. This research will show that individual participants do not approach the search task in separate FOVs using a windshield wiper pattern.

This study shows that current combat simulation models use search and target acquisition methods that are inconsistent with human behavior. A large FOR divided into uniform FOVs is not representative of an individual soldier's sector of responsibility (U.S. Army, 2007). Preset patterns such as parallel sweeping or windshield wiper

patterns do not accurately portray human behavior and can drastically affect the outcome of a simulated battle. This research shows that regardless of the size of FOR or FOV, humans do not systematically sweep back and forth across a sector of responsibility. Human participants instead search for specific objects, such as windows and doors, where targets are more likely to occur (Hoffman, 2000). Such erroneous outcomes are detrimental both to soldiers using the model for training and to commanders who use the model for planning. Furthermore, current models do not address how additional situational awareness can alter the search behavior of individual entities.

3. Current Army Search Doctrine

U.S. Army doctrine does not address search in urban terrain in a sufficient manner. The Army's Urban Operations manual limits the discussion to the challenges of target acquisition in urban terrain. For example, it explains how additional cover and concealment limit exposure time of targets and makes them more difficult to identify, but it does not offer a technique for searching urban terrain more effectively (U.S. Army, 2006).

Chapter 8, Urban Areas, of FM 3–21.75: *The Warrior Ethos and Soldier Combat Skills*, simply discusses movement techniques, entering a building, and clearing a room. Soldiers require each of these crucial skills for successful urban operations; however, this chapter does not discuss search or target acquisition in urban terrain. Chapter 9, entitled *Every Soldier is a Sensor*, describes three daylight visual search techniques. *Rapid scan* is a pattern in which the soldier searches 100 meter overlapping strips of terrain from left to right, near to far, until the entire sector is covered. *Slow scan* implements the same pattern as rapid scan with slower and more deliberate side to side movement. If the soldier finds no targets with rapid and slow scans pictured in Figure 2, he then uses *detailed search*, which depends on dividing the sector of fire into smaller sectors. The soldier then incrementally searches small areas with frequent pauses (see Figure 3). This search pattern relates closely to the search technique implemented in combat simulation models. Each of these search techniques are sufficient for rural terrain, but they do not address the additional complexity in an urban environment (U.S. Army, 2008).

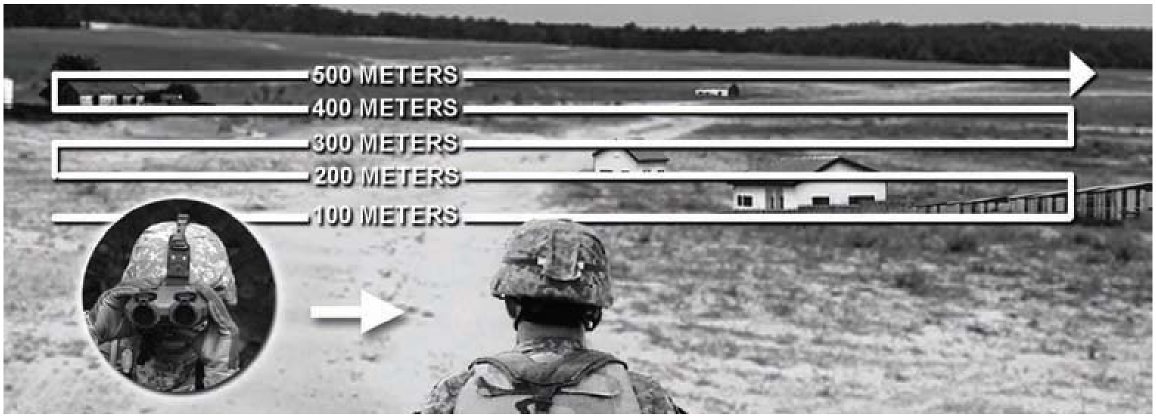

Figure 2. Rapid and Slow Scan Pattern. [From U.S. Army, 2008]

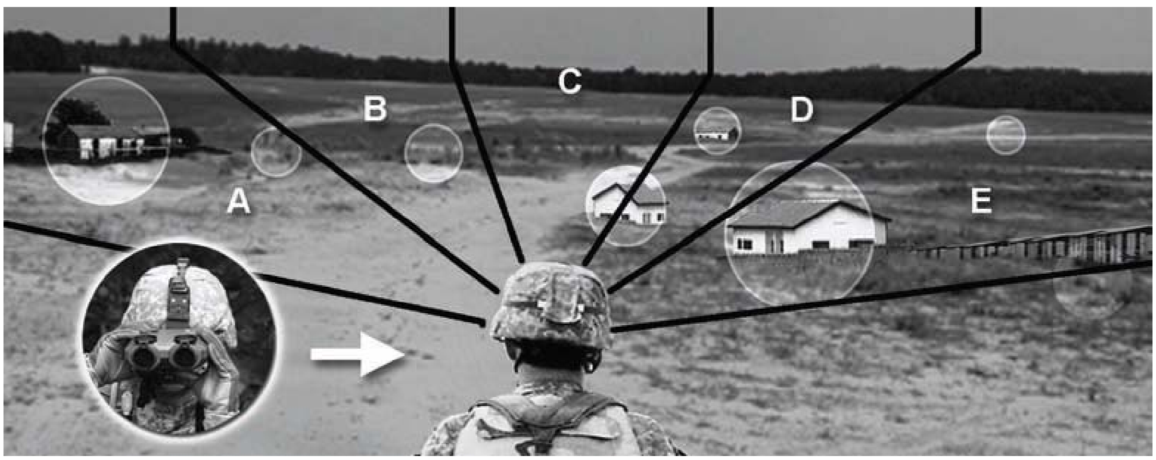

Figure 3. Detailed Search Pattern. [From U.S. Army, 2008]

The rifle marksmanship manual (FM 3–22.9) also recommends three search methods. The soldier employs the self-preservation method when he moves into a new area. He quickly scans the area for enemy activity and immediate danger glancing at specific points throughout the area. This method closely resembles the technique proposed in this thesis; however, the manual does not specify this method as an urban search technique. The 50-meter overlapping strip method is identical to the rapid and slow scan patterns discussed previously with the exception that the strips are 50 meters instead of 100 meters. Maintaining observation of the area is the last method in which the soldier glances quickly at various points throughout the entire area, focusing the eyes

on specific points. The only discussion regarding urban terrain includes specific firing positions. The manual proposes no unique urban search techniques (U.S. Army, 2008).

The Tank (U.S. Army, 2005), Bradley (U.S. Army, 2003), Scout (U.S. Army, 2005), and Stryker (U.S. Army, 2006) Gunnery manuals each offer the same two daytime visual ground search techniques. The Rapid Scan begins with the soldier oriented in the center of the sector and rapidly scanning near to far. The soldier then orients to the left or right and conducts a similar rapid scan from near to far, overlapping the center sector. Finally, the soldier orients to the opposite side and conducts the same scan. Slow scan is a method which is identical to the 50-meter overlapping strip method referenced from the marksmanship manual above. Only the Tank Gunnery manual briefly discusses the difficulties of target acquisition in urban terrain, however, it does not discuss a search technique.

The search techniques referenced above are sufficient for operations in rural terrain, but recent conflicts such as those in Somalia, Bosnia, Kosovo, and Iraq demonstrate a trend toward combat in urban environments. Rural environments consist of homogeneous natural terrain such as rolling hills, trees, brush, and open fields. Conventional combatants are typically well camouflaged in rural terrain, and therefore search techniques require a more systematic approach. Such methods are not sufficient for the complex nature of urban operations. Increased stimuli or clutter combined with the three dimensional aspect of urban terrain require more than simple two dimensional scanning patterns. Search techniques in urban terrain must account for man-made objects with more occlusions. The enemy can be anywhere in a rural environment. In the urban environment, he is more likely to present himself in windows, doorways, behind objects such as cars or the sides of buildings, or on rooftops. A preset search pattern results in wasted search effort for viewing locations at which a target is not likely to be present such as an empty parking lot with no occlusions.

The focus of this research is to model human search behavior, not an optimal search pattern. This thesis proposes recommendations for Army doctrine that are based on professional military participant fixation data and do not account for detection performance. Additional research for improving Army doctrinal urban search techniques

may incorporate domestic law enforcement procedures. Such agencies routinely conduct operations in urban terrain. Although the scenarios and targets may differ drastically, domestic law enforcement urban training techniques may provide valuable insight.

C. OBJECTIVES

Combat simulation models are beneficial for both training and analysis, and as a result their use is widespread. Reliability of such models can be suspect simply because of the countless variables associated with humans and the decisions they make. This research aims to augment existing approaches for the search process by incorporating a model of human search behavior and the role of additional situational information. It also seeks to lay the foundation for future research to introduce new doctrinal search techniques in urban terrain.

D. MODELING APPROACH

This research relies on experimental eye tracking data, described in Section II, from which fixation determination results. A fixation, in the context of eye movement analysis, is a pause on a portion of the image which provides information. A saccade is the rapid movement between fixations from which no information results (Salvucci & Goldberg, 2000). Separating data points into fixations and saccades is the first step to building the model.

As with any analysis of eye tracking data, fixation determination is critical. This study begins with an appropriate fixation identification algorithm and parameter selection. Selecting a fixation identification algorithm with acceptable parameters is crucial to determine where, when, and at what the participant is looking. Various fixation identification algorithms and parameters can easily lead to different interpretations of the same data (Shic, Scassellati, & Chawarska, 2008). For example, increasing the velocity threshold parameter in a velocity-based fixation identification algorithm results in more fixations. An unfortunate result of such a change is, for example, a saccade falsely labeled as a fixation point, which results in incorrect analysis. It is clear that this one parameter can introduce uncertainty in any analysis which relies significantly on fixation points.

Once the selected fixation identification algorithm adequately determines the fixations, fixation analysis occurs for each scene across all participants. Fixation frequency and order then determine the probability of searching a cell within a discretized scene. Mouse click data determine the probability of detecting a target in a cell given a fixation in that cell. This data provides a probability of detecting each target as well as a probability of a false positive detection.

This thesis applies Myopic Allocation of Search Effort to model an individual's visual search pattern. The average fixation size across all participants on each scene determines the size of the discretized regions. The fixations and detection statistics form the basis of the prior probability map. The model uses Bayesian inference to update the posterior probabilities after each small increment of search effort. Experimental data provides the basis for comparison of the proposed model with current combat models. This information is the basis for recommendations to improve search in combat simulation models and to recommend future research to propose search techniques for U.S. Army doctrine.

In addition to formulating a realistic model for the search pattern, this thesis investigates the value of contextual information and its effect on search performance. The information provided to participants is in the form of visual situation reports (SITREPS) and verbal size, activity, location, unit, time, and equipment (SALUTE) reports. This research investigates the effect a SALUTE report has on detection probabilities and search patterns.

E. LIMITATIONS

There is significant literature on the neurological approach to finding objects in a scene. Such research seeks to determine how to find objects in a scene based on the characteristics of the scene and the object. This thesis uses a statistical approach to determine where and in what order participants search a scene. Determining at what the participant is gazing is left for future research.

This study focuses on one individual participant viewing one static scene at a time. At no time does a soldier face an enemy as an individual in a combat situation.

The modern U.S. Army warrior operates as a member of a team, squad, platoon, or company. The field of view displayed in the study is not representative of an individual's actual sector of responsibility. The modern warrior is responsible for a much more narrow perspective, so that he can pay it the necessary level of attention (U.S. Army, 2007). Urban terrain consists of a vast variety of stimuli such that one individual could not possibly be responsible for such a wide three-dimensional area. He would instead be responsible for a smaller portion of the area. Additional study should focus on the interaction of multiple individual soldiers working in concert.

The experiment requires participants to locate hostile targets in urban terrain. The instructions to the participants indicate that all targets in the scene are considered hostile. A critical aspect of target acquisition is target identification. This study does not require the participants to identify potential targets as hostile or non-hostile individuals.

F. CONTRIBUTIONS

This work contributes to the field of human visual search in two main areas. The first result is a deeper understanding into the process by which human participants develop a search pattern based on top-down, target-directed search. The second result is a new application of search theory to model human search behavior, which shows an improvement on current techniques.

This thesis shows that, in the context of a target-driven search task, human participants do not search in a random pattern. Despite the lack of a single distinct search pattern among all participants, this study shows that participants tend to repeatedly bias similar scene locations when searching for specific stimuli. This behavior indicates that the search process is a function of the environment. Participants search for objects within the urban scene in which human targets are most likely to exist. Participants expend the vast majority of search effort on objects such as windows, doors, behind walls, and on roof tops. Furthermore, the participants prioritize this search effort to maximize the likelihood of locating such targets. This prioritization is evident through the examination

of fixation ordering and results in an efficient use of search effort. This research also shows that the addition of contextual information affects search priority and drives the search behavior in favor of the additional information.

The second important finding implements the understanding derived in the previous paragraph to develop a model to predict human search behavior. This thesis reflects a novel approach for modeling human search behavior in naturalistic scenes, and highlights the shortcomings of current simplistic models. This work presents a rigorous application of search theory, utilizing probability models of visual stimuli and prior information, and expands its relevance to modeling of human cognitive behavior. The result is a statistical model, which reflects human search priorities and incorporates the effect of added situational awareness.

G. RELATED WORK

Navalpakkam and Itti formulate visual search as an optimization problem and compare the optimal strategy to human subjects. This formulation seeks to maximize the salience of a target relative to distracters using the signal to noise ratio. They find that humans select visual cues to maximize the signal to noise ratio between targets and background (Navalpakkam & Itti, 2006). The Myopic Search Model proposed in this thesis is based on the fact that humans will search in a manner to maximize the probability of detection for each look. Instead of focusing on characteristics of a given image, this thesis provides a higher level search model in which issues such as image saliency may be encompassed.

Vogel and de Freitas implement a model which is very similar to the Discrete Myopic Search model proposed in this thesis. They propose a model to optimize the sequence of gazes using bottom-up saliency and top-down target information. The model uses a Bayesian sequential decision process to determine gaze sequence. The sequential gaze planning begins with a prior probability distribution over all object locations. The model updates this distribution after each gaze and the result is a policy, or sequence of gazes, based on the most promising locations. Although top-down target information clearly plays a key role in participants' search patterns, the Discrete Myopic Search

model is statistically based on participant fixations and does not directly consider bottom-up saliency or top-down information when constructing the gaze sequence. Vogel and de Freitas implement their model with state-of-the-art object detectors to locate monitors and computer screens within cluttered images. This is in contrast to this thesis, which focuses on modeling human behavior rather than determining the optimal search technique to locate objects (Vogel & de Freitas, 2008).

Chung and Burdick propose a "Saccadic" Search strategy, which implements a Bayesian framework to update belief probabilities across a discretized region after each discrete time step. A cell belief probability represents the searchers belief that a target resides in that cell. This search strategy allocates search effort to the cell with the highest belief probability for each discrete time step, similarly to the Discrete Myopic Search model (Chung & Burdick, 2007). Despite the similarities with the Discrete Myopic Search model proposed in this thesis, the search model presented by Chung and Burdick is a probability model for search using a mobile robot and assumes only a single target. The Discrete Myopic Search model is a probability model for human visual search of images which may contain multiple targets.

Jungkunz proposes a model for predicting eye fixations based on relevant scene locations. Relevant scene locations, in the context of his work, include such locations where human targets can seek cover behind walls, in windows, and in doors as well as locations where targets can hide from view. He develops a relevance map based on such locations for comparison with human participant fixation data. He then combines the relevance map with a salience map for improved results (Jungkunz, 2009). The relevance map is similar to the prior probability map constructed in this thesis. The Discrete Myopic Search model, however, produces a fixation pattern based solely on a portion of the participant data. Although the Discrete Myopic Search model tends to fixate on similar relevant scene locations as described above, it is not designed specifically to do so, nor does it overtly examine the contributions of bottom-up and top-down information.

H. THESIS ORGANIZATION

The remainder of this thesis is organized as follows:

- Chapter II: Formulation. This is the formulation of the visual search problem to include a description of the experiment.
- Chapter III: Modeling Allocation of Visual Search Effort. A thorough description of the Discrete Myopic Search model and its application to the visual search problem.
- Chapter IV: Results and Analysis. Statistical analysis of the Discrete Myopic Search model compared to the windshield wiper representation of current combat simulation models.
- Chapter V: Conclusions and Recommendation. Discussion of the implications of experimental results on the search process in current combat simulation models as well as current Army doctrine and recommendations for future research.

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II. FORMULATION

This chapter describes a method which is one portion of a two tiered Situational Awareness / Search and Target Acquisition (SA/STA) experiment designed to investigate SA/STA aspects of current combat simulation models. Modern soldiers posses vast amounts of technology which provides them a high level of situational awareness. The U.S. Army Training and Doctrine Command Analysis Center Monterey, CA (TRAC-Monterey) developed this experiment to better understand the role of this additional situational awareness on STA. The methodology of the project begins by conducting a background study to define the problem and refine the independent variables. The next phase is the conduct of the experiment. Finally, TRAC-Monterey will, in conjunction with this thesis, analyze the data to develop an algorithm for testing and implementation. Critical study issues include determining how a soldier scans for targets and the effect of information and cues on STA.

Tier 1 of the experiment consisted of static and dynamic stimuli and was conducted at the Naval Postgraduate School. Tier 2 also consisted of static and dynamic stimuli; however, it was conducted in a battle lab virtual environment at Fort Benning, GA. The ultimate objective is to develop and algorithm for implementation into current simulation models. Funding for this project is provided by the Soldier Focus Area Collaborative Team (FACT) with additional funding from the Office of the Deputy Chief of Staff G–3/5/7, Modeling and Simulation Directorate.

TRAC-Monterey is responsible for the overall project execution. The Modeling, Virtual Environments, and Simulation (MOVES) Institute at the Naval Postgraduate School developed the stimuli for the 16 scene images analyzed in this thesis and assisted in the execution of the experiment. The Operations Research-Human Systems Integration Program at the Naval Postgraduate School assisted in constructing and validating the experimental conditions.

This thesis focuses on the tier 1 static data to formulate the visual search problem as an optimization model. Each discrete step of the model allocates a small amount of

search effort to a portion of the image, which maximizes the probability of detecting a target. The overall probability of detecting targets in each scene increases with each discrete look. The experimental data provide the inputs to the model.

The experiment data from 13 participants comprises a training set while the remaining six participants' data forms a test set. The data from the training set builds the detection probabilities and fixations for the model. The data from the test set forms the basis for comparison of the existing model data with the proposed model data.

A. METHOD

1. Participants

Nineteen participants volunteered for the experiment understanding that no compensation results from their participation. Participants are all members of the U.S. Military and each had some level of search and target acquisition training. Eleven participants represent the U.S. Army's Infantry, Engineer, Artillery, Ordinance and Aviation branches. Five participants represent the U.S. Navy and three represent the U.S. Air Force.

All 19 participants are males. Three participants are left handed and the remaining 16 are right handed. The maximum participant age is 52, the minimum age is 26, with a mean participant age of 35.42 ± 5.34. Participants served an average of 13.69 ± 5.95 years in the military. Twelve participants have deployed to a combat zone, six of which conducted foot patrols and 11 of which conducted vehicle patrols. Nine participants report having specialized search training. Thirteen participants report some experience with first person shooter video games.

2. Equipment

The entire experiment is conducted on a Dell XPS 720 with an Intel Core 2 Quad 2.40 GHz processor. The scene images display on a large high resolution Dell monitor. Participant inputs occur through both a standard Dell keyboard and a standard two button mouse. The fixation data is collected on a Seeing Machines faceLAB4 eye tracking

device (Seeing Machines, 2006). The device records gaze direction through two digital cameras positioned on the desk in front of the participant with each oriented at one of the participant's eyes.

3. Stimuli

There are a total of 16 scenes and the number of targets in each scene ranges from zero to five. The experimental design ensures that scene presentation is random for each participant. Targets may be completely exposed or partially occluded, standing, kneeling, or lying in the prone position. Eight scenes have movement (described below), eight have SITREPS, eight have SALUTE reports, and eight have Mini-Maps. Table 1 displays the variables for each scene.

Scene Number	0000	0002	0012	0019	0020	0021	0024	0027	0033	0035	0040	0041	0042	0043	0044	0045
Total Targets	2	5	2	3	4	0	4	0	3	2	3	1	3	3	2	3
Movement	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
Mini-Map	1	0	0	0	1	1	0	1	1	1	0	1	1	0	0	0
SALUTE	1	1	1	0	1	0	0	0	0	0	1	1	1	1	0	0
SITREP	1	1	0	1	0	1	0	0	0	1	1	1	0	0	1	0
SALUTE to Movement	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0

Table 1. Scene variables designed to explore changes in the search and target acquisition process.

Movement in a scene consists of one target appearing and then disappearing from the scene. The movement occurs from behind objects in the scene, in windows or doors, or from behind walls. In each case, the target enters the scene after approximately one second remains exposed for approximately two seconds and then exits the scene.

The SITREP is a static scene which the participant views before he views the scene itself. It provides information to include the participant's location and orientation in the scene, an overhead schematic of the terrain, and likely enemy actions. The

participant may glean insight into probable enemy locations based on the SITREP. The SITREP scene displays until the participant is satisfied and informs the experimenter that he is prepared to continue. Figure 4 is an example SITREP for scene 0000.

The SALUTE report is a verbal alert, which refers to a target in the scene. Each SALUTE report is accurate and provides information regarding the location of a specific target. An example SALUTE report for scene 0000 displayed in Figure 5 is: “Look at the window on the left. I think I see a helmet.” The SALUTE to Movement row in Table 1 highlights SALUTE reports which refer to a moving target. Only one SALUTE report refers to a moving target in this experiment.

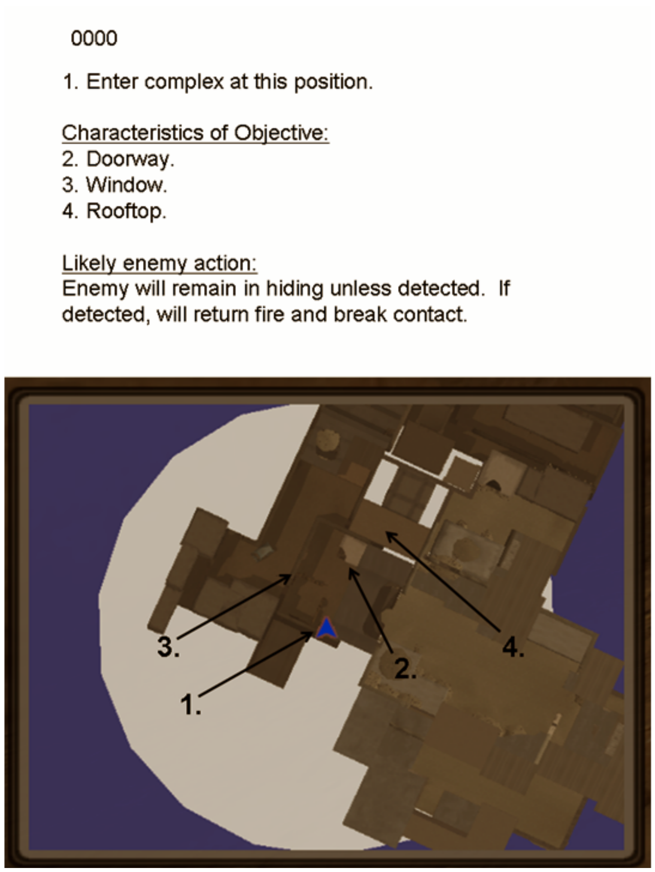

Figure 4. This SITREP for Scene 0000 includes the participant’s location, key terrain, and an enemy course of action (See Appendix A for Scene 0000).

Figure 5 is an example scene with a mini-map. The mini-map is an overhead schematic of the scene identical to the schematic from the SITREP. It provides a layout

of the terrain and the location and orientation of the participant relative to the scene. There is no text on the mini-map to highlight key terrain or an enemy course of action. It always appears in the lower left corner of the image and remains for the duration of the scene.

Figure 5. Example Scene 0000 with mini-map in the lower left corner. The small blue triangle in the mini-map represents the participant's location.

4. Experimental Protocol and Procedures

Experimenters greet and thank each participant upon arrival. The participant then reads and signs a consent form and completes a participant questionnaire. Experimenters then administer two tests to ensure proper color vision and visual acuity. The first test is for color deficiency using the Ishihara's Test For Color Deficiency 24 Plates Edition. This test ensures that participants can properly discriminate targets from the background. The second test is to ensure that the participant has a minimum of 20/40 uncorrected visual acuity. Reflections in contact lenses or glasses can obscure the eyes, which may produce poor eye tracking results, so it is critical that the participant's vision is uncorrected (Seeing Machines, 2006).

The next procedure is to calibrate the eye tracking device. This requires the physical adjustment of the equipment to account for the various participant heights as well as the calibration of the digital cameras and software. Calibration is necessary for each participant because the eye tracking device reads the individual's facial features and eye movements.

Experimenters then orient the participant to the equipment and provide instructions on the conduct of the experiment. The instructions include a brief scenario, which provides a background for the scenes. The participant has 20 seconds to scan each scene and he can advance the scene prior to the 20 seconds if he is confident that he has found all targets. The instructions inform the participant that there are between zero and six targets in each scene. The participant indicates a target detection by depressing the left mouse button on the stimulus which he believes to be a target. The participant then practices using the experiment equipment on an example scene. Once the participant is comfortable with the example scene, the experiment begins.

B. FIXATION DETERMINATION

1. Data

Data understanding and preparation are crucial steps to performing effective analysis. The experiment produces raw data in the form of three separate files for each participant. The eye tracking device produces the first file, which contains numerous columns of data for each frame. Each frame is approximately 16 milliseconds. The pertinent data for this study is the x and y pixel coordinates of the intersection of the participant's gaze with the screen. The second file contains all participant inputs and scene information with the associated CPU time. The third file correlates each frame to the CPU time to assist with synchronization of the first and second files. User inputs are mouse clicks, which register as a correct hit or false positive detection. The computer records the time and x and y coordinates of each user input. The scene information includes the scene name, the number of targets in each scene, the time each scene is advanced, and misses when the participant fails to click on a target. Before fixations are

determined, information from each of these files must be fused together so that data points are associated with the proper time and all information falls within the proper scene.

SITREP and SALUTE scenes provide additional information to the participant prior to the onset of certain scenes. Blank scenes serve as a primer for all relevant scenes in order to prevent improper fixations at the beginning of any given scene. This information is important because the eye tracking device records data to the output files for these scenes, but these data are not relevant to the study.

A new file results by combining the three original files for each participant. This file is organized in ascending order of machine time for each possible event. This file retains all data points, to include the irrelevant points between scenes. The next step is to extract only the pertinent information from the file. The VisDataSearchExtract code (see Appendix B) performs this extraction to determine fixations and compile user input data.

2. Fixation Identification Algorithm

There are several algorithms to determine fixations and each has associated advantages and disadvantages. This study implements a velocity-based algorithm called Velocity-Threshold Identification (I-VT). This algorithm is particularly desirable for this study because it requires only one parameter, is very efficient, and runs in real time (Salvucci & Goldberg, 2000). The algorithm simply labels data points with a velocity below the threshold as fixation points and data points above the threshold as saccade points. Fixations result by collapsing consecutive fixation points. Figure 6 is a visual representation of fixations and saccades derived from the I-VT algorithm (see Appendix A for original scene image). The yellow dots represent saccade points, the green dots represent fixations points and the blue circles are fixations with the fixation number inscribed in black text. The targets are highlighted in red for the benefit of the reader.

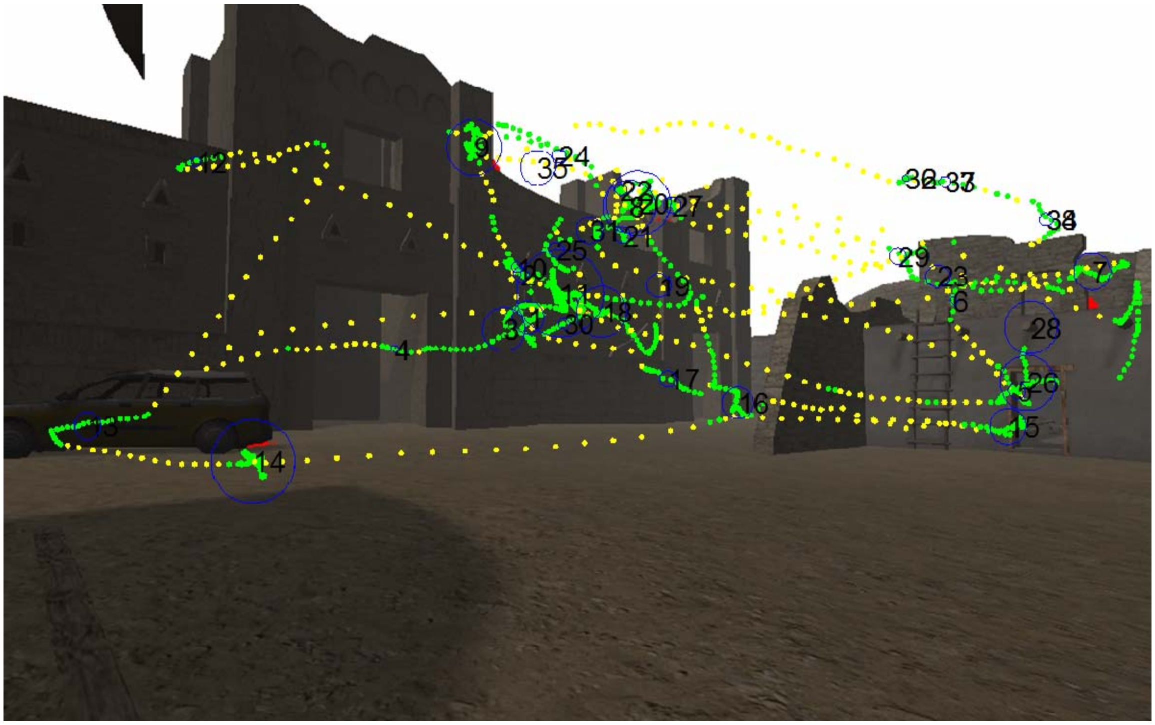

Figure 6. Visual representation of participant 11's fixations in Scene 0002. The yellow dots represent saccade points, green dots represent fixation points, blue circles represent fixations, and the black text indicates the fixation number. The targets are highlighted in red.

It is necessary to smooth the data with a filter because velocity based algorithms are sensitive to noise, particularly for data points near the threshold value (Salvucci & Goldberg, 2000; Munn, Stefano, & Pelz, 2008). The algorithm uses a moving average over 15 data points. In addition, fixations require a minimum of five fixation points. This also prevents noise along the velocity threshold by eliminating single points which fluctuate between saccades and fixation points.

The point to point velocity between two gaze points is determined by using the forward difference approximation $f'(x) = \dfrac{f(x+h) - f(x)}{h}$ where *f(x)* is the pixel location of the participant's gaze and *h* is the time between frames (Blackmon, Ho, Matsunaga, Yanagida, & Stark, 1997). The measure of velocity is in degrees per second; therefore, some computation is necessary to convert the values from pixels per frame. In this experiment, one degree corresponds to approximately 48 pixels and, at 60 frames per

second, one frame lasts approximately 16.67 milliseconds in duration. The resulting conversion of one degree per second yields a velocity of approximately 0.8 pixels per frame. Since the point to point velocities are easily approximated using the forward difference, an appropriate value for the threshold is inferred based on the data and exploratory data analysis (Salvucci & Goldberg, 2000). The result is a velocity threshold value of 0.8 pixels per millisecond or 16.67 degrees per second. Figure 7 compares the frequency of various fixation sizes for velocity threshold values of 0.4, 0.8 and 1.2 pixels per millisecond. The comparison displays similar distributions for each velocity threshold value and shows that small changes in the value do not affect the analysis.

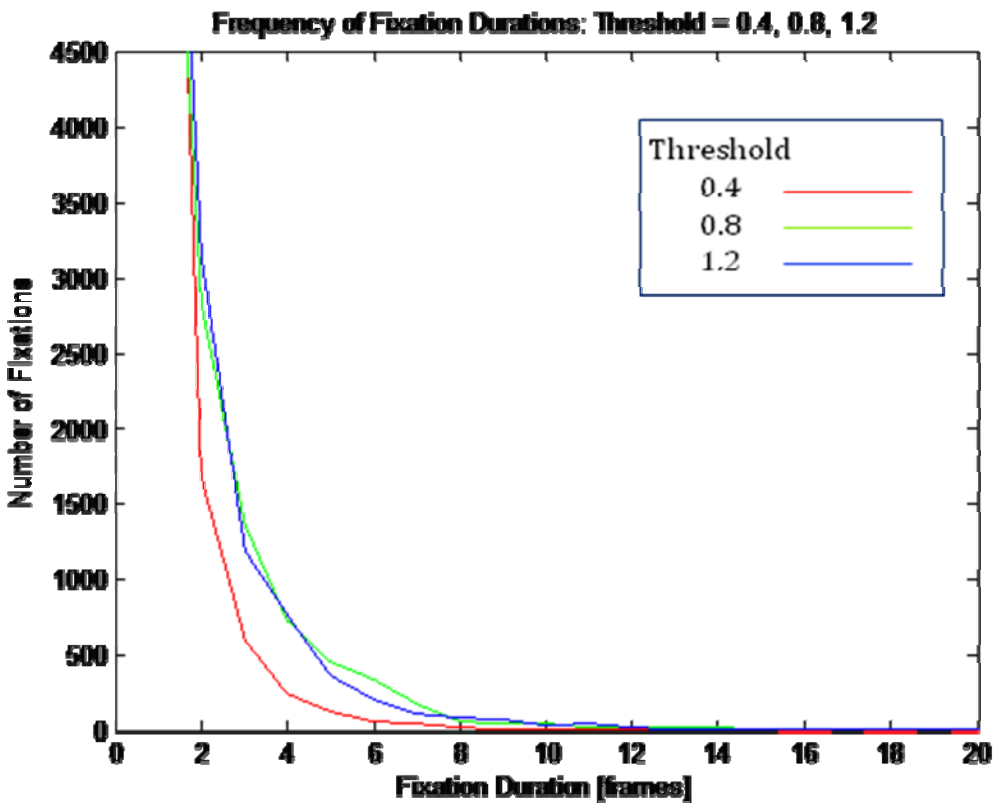

Figure 7. Comparison of frequency of fixation durations of velocity thresholds.

C. DETECTION STATISTICS

The detection statistics lay the foundation for the prior probability map and thus are essential to the study. The probability of detection for each target results by dividing the number of detections for each target by the number of participants. This information forms the likelihood function displayed in Table 2.

x \ y	Probability of Detecting 0 Targets	Probability of Detecting 1 Target	Probability of Detecting 2 Targets	Probability of Detecting 3 Targets	Probability of Detecting 4 Targets	Probability of Detecting 5 Targets
0 Targets in Scene	1	0	0	0	0	0
1 Target in Scene	0.6923	0.3076	0	0	0	0
2 Targets in Scene	0.1538	0.4038	0.4423	0	0	0
3 Targets in Scene	0.0897	0.1282	0.4358	0.3461	0	0
4 Targets in Scene	0	0	0.0769	0.4230	0.5	0
5 Targets in Scene	0	0	0	0.1538	0.7692	0.0769

Table 2. Likelihood function *p(y|x).*

The likelihood function is the conditional probability of detecting a specified number of targets given the total number of targets in the scene. For example, there are six scenes with three targets each. This means that there are 6 * 19 = 114 opportunities for a participant to detect zero to three targets in a scene with three targets. The probability that zero targets are detected in a scene with three targets is Pr(y=0|x=3) = 0.0897, which is the entry at (4,1) in Table 2.

III. MODELING ALLOCATION OF VISUAL SEARCH EFFORT

A. DISCRETE MYOPIC SEARCH MODEL

Discrete Myopic Search is a search technique, which optimizes the probability of detecting a target for each of *k* discrete observations. The given search area is discretized into *n* cells in which a probability that a target is within the i^{th} cell, denoted p_i, is assigned. Each successive look in cell *i* has a probability q_i of not detecting the target and this probability is assumed independent of all other looks. Given k_i looks in the i^{th} cell, the model optimizes the probability of detection $p = \sum_{i=1}^{n} p_i(1-q_i^{k_i})$ subject to $k_1 \geq 0$ and a constraint on $\sum_{i=1}^{n} k_i \leq K; k_i \in (0,1,...,K)$ for *n* cells (Washburn, 2002).

The model implements a greedy algorithm in which the $k+1^{st}$ look is allocated to the cell with the greatest increase to the overall probability of detection. The increase in probability of detection in the i^{th} cell is given by:

$$p_i(1-q_i^{k_i+1}) - p_i(1-q_i^{k_i}) = p_i(1-q_i)q_i^{k_i}$$

This implementation produces an optimal allocation of discrete looks because $p_i(1-q_i^{k_i})$ is a concave function of k_i (Washburn, 2002). A critical assumption to ensure concavity and the optimality of the resulting search pattern is the absence of false positive detections. Given the context in which false alarms, such as engaging a civilian, would incur a prohibitively high penalty, the assumption of no false positive detection errors is considered reasonable. Further research, either psychophysical or otherwise, is left for future study.

Common applications of a Myopic Search model include anti-submarine warfare and Coast Guard search and rescue. A historic example is the search for the sunken USS Scorpion in 1968. Searchers constructed a prior probability map as a composite of nine

separate priors. Searchers developed the nine priors based on different scenarios explaining how and where the sinking occurred (Wagner, Mylander, & Sanders, 1999). This thesis proposes a novel application of this model in the form of visual search.

This study slightly modifies the model to accommodate zero to six targets. Normalization of the prior probability map ensures that the sum of all cells equals one. If a detection occurs, the cell or cells in which the detected target resides are eliminated from future consideration. This change allows the model to find the optimal search pattern with multiple targets.

B IMAGE PREPARATION

1. Image Discretization

Discretization of each scene into appropriately sized cells is the first step in implementing the Discrete Myopic Search model. Discretization allows for the careful investigation each participant's fixations and provides some robustness to error in the eye-tracking hardware. The size of each cell is determined by the average fixation size across all participants for each scene. This mapping of fixation size to cell size is given by $f(\overline{fix}) = l$ where $\overline{fix} = \frac{\sum_{i=1}^{n} fix\_size_i}{n}$ for n fixations in a scene across all participants and l is the length of each side of the cell. Fixation size is determined by the time duration of the fixation. The interpretation of this implementation of fixation size is that the longer a participant gazes at a particular portion of the image, the more stimuli are present in that area. As such, l is assumed to increase linearly in relation to $\overline{fix}$ in order to account for the increase in stimuli in that cell. Figure 8 is an example of a discretized scene. Scene 0000 has an average fixation size of 76 pixels, which results in 375 square cells.

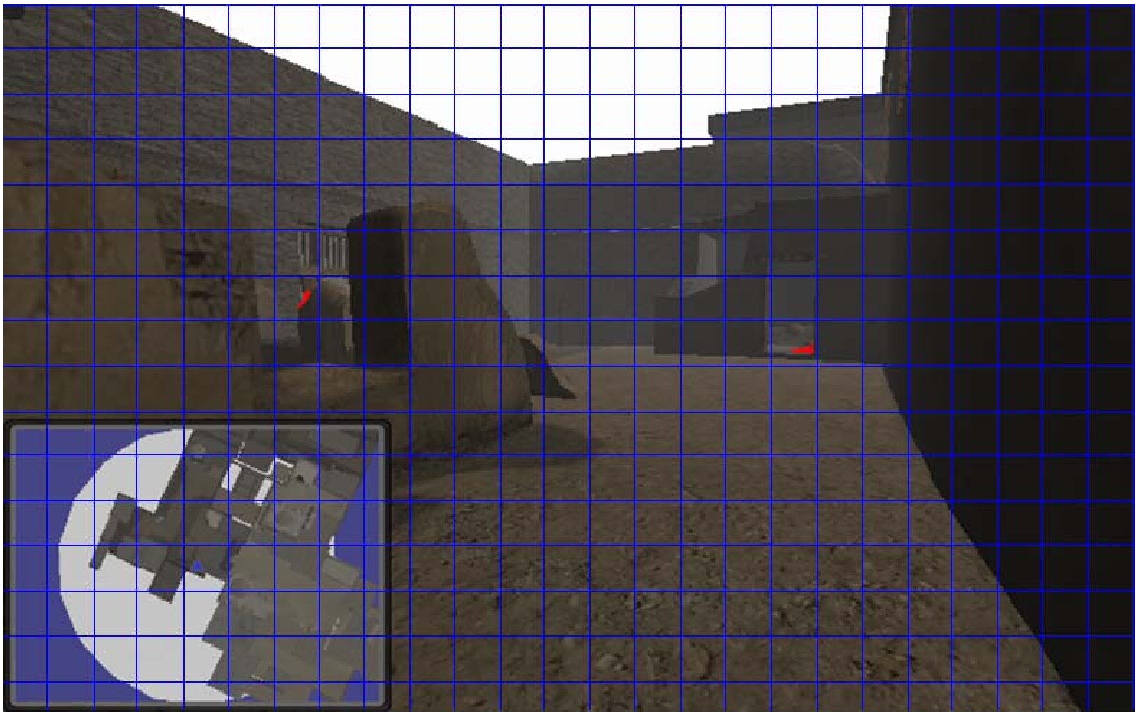

Figure 8. Scene 0000 discretized.

2. Weighting Fixations

The objective of this research is to develop a model to predict an individual's search pattern. The hypothesis is that an individual will search in a manner in which to optimize his ability to detect targets during each successive fixation. He prioritizes his fixation pattern based on where he believes targets will most likely be located. This also corresponds to proposed schemes, such as saliency-based methods for visual attention in which the scan pattern is prioritized based on decreasing saliency (Itti & Koch, 2001). Since participant fixations determine the prior probability map, it is necessary to prioritize the fixations using weights.

Search performance is not constant even over a short period of time (Cooke, 1983). This rate of change is not well defined, but can be estimated from the experimental data. As a participant locates targets or fails to locate targets, his belief that targets remain in the scene decreases. A histogram of detections over time, Figure 9, displays a pattern of search performance.

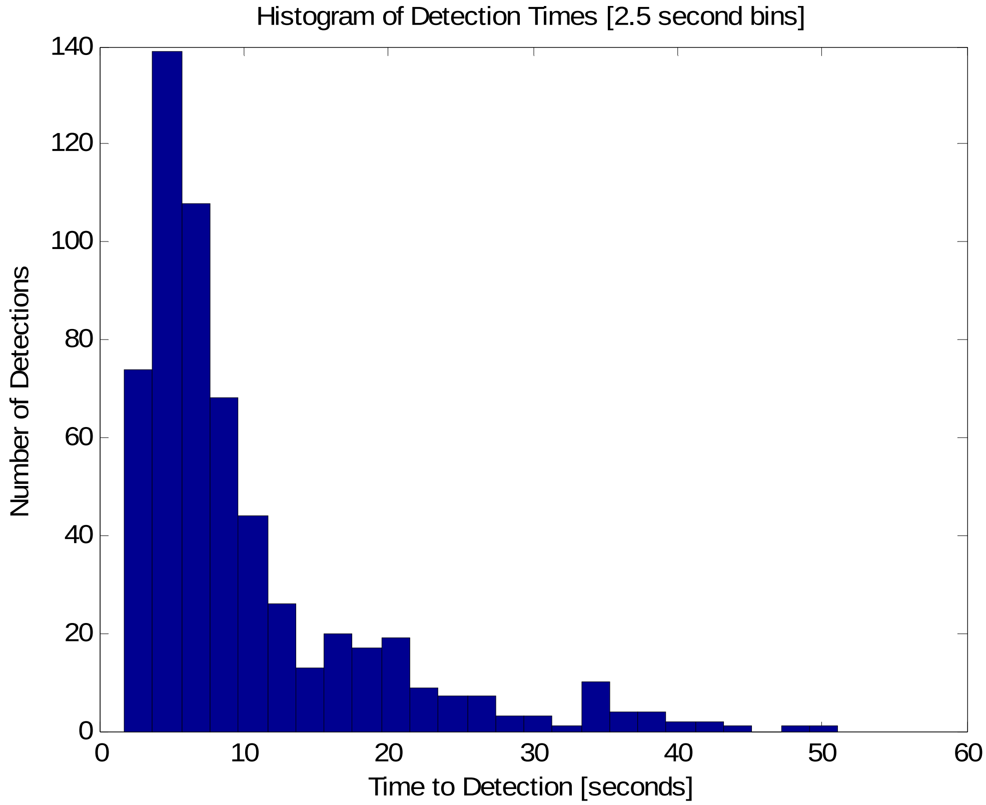

Figure 9. Search performance over time indicates a rapid transition from initial fixations when the scene is first presented to initial detections. The detections then decrease non-linearly as time progresses.

This representation of search performance closely resembles a Gamma distribution, as supported by existing literature regarding detection times during visual search tasks (Wolfe, Torralba, & Horowitz, 2002). This distribution, illustrated in Figure 10, becomes the basis for weighting the order of fixations by participant. The value for each fixation is given by $\frac{1}{\beta^{\alpha}\Gamma(\alpha)}x^{\alpha-1}e^{-x/\beta}$ where x is the fixation order by participant $\alpha = 2$ and β varies based on the number of targets in the scene. Increasing β with the number of targets in the scene provides a higher value to more of the initial fixations. This allows the model to adjust for the increase in visual stimuli and to account for additional fixations on target locations. The initial fixation typically occurs towards the center of the scene when the scene initially advances. The peak represents the transition from the initial fixation to the first detection and maps to the peak in Figure 9.

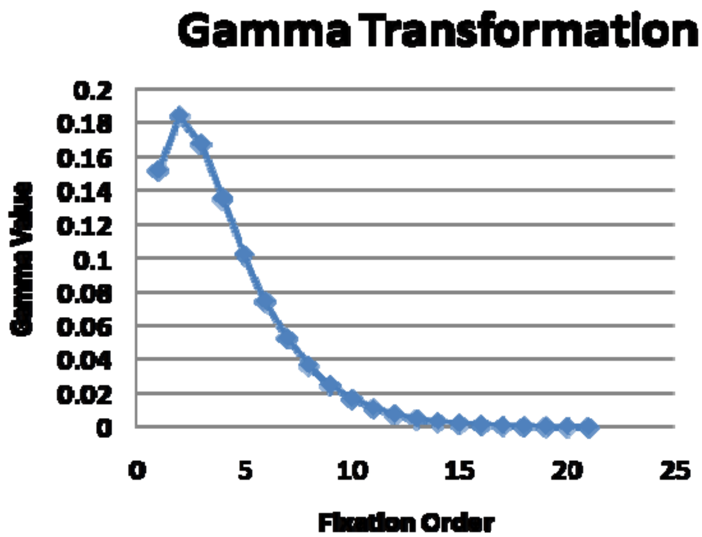

Figure 10. Gamma weights for participant 11's fixations in scene 0000.

3. Prior Probability Map

Both the probability distribution of target locations, p_i values, and the probabilities of not detecting the target given a look in cell *i*, q_i values, are derived from the data. There is one *p* value and one *q* value for each cell in the discretized image resulting in two matrices. Probabilities are assigned to *p* based on the sum of the weighted fixations within each cell. These values are normalized so that the sum of all cell values in a scene equals one. Probabilities are assigned to *q* based on the detection statistics. Since the values in *q* are the probabilities of not detecting the target given a look in that cell, the values in *q* are 1-Pr(target detection) for each cell. Figure 11 displays scene 0000 discretized with each fixation location highlighted in yellow.

Scene discretization, the weighting of each fixation, and the mapping of each fixation to the appropriate cell builds the *p* matrix and the prior probability map. Figure 12 is a three dimensional representation of the prior probability map for scene 0000. The height of each cell represents the probability that a target exists in that cell. The color of each cell indicates the height of that cell in relation to other cells. "Hot" red colors transition to "cool" blue colors to indicate the transition from tall peaks to short peaks, which represents the transition from higher probabilities to lower probabilities. The

Discrete Myopic Search model allocates search effort to the highest peak for each discrete look. Note how the concentration of fixations around the window on the left and the door on the right in Figure 11 closely resembles the probability distribution in Figure 12. This scene has a SALUTE, which draws the participants' initial attention to the left target. The larger concentration around the window is a result of heavier fixation weights for earlier fixations. The model shows a concentration of probability in the center of the scene as well. This small mass of probability is a result of scene transition when most participants' gazes are towards the center. The value of the cell in which the model allocates search effort decreases after each look. This occurs because the more effort that is placed into a given cell with no detection, the lower the probability that a target exists in that cell.

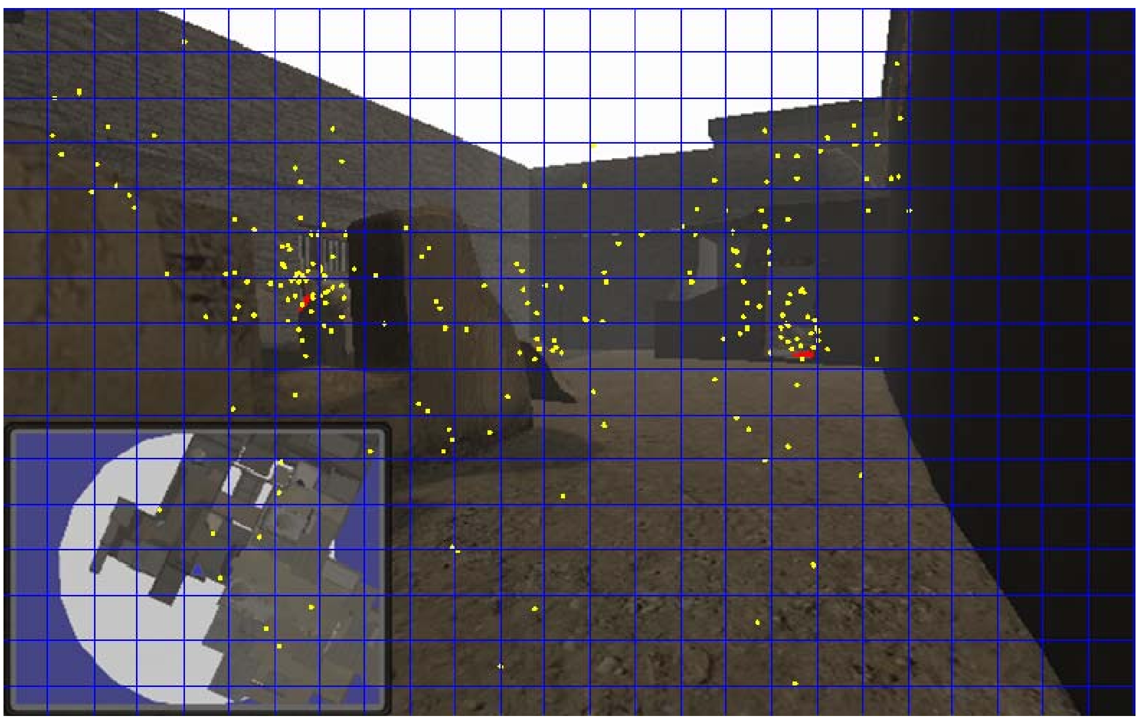

Figure 11. Scene 0000 discretized with fixations superimposed.

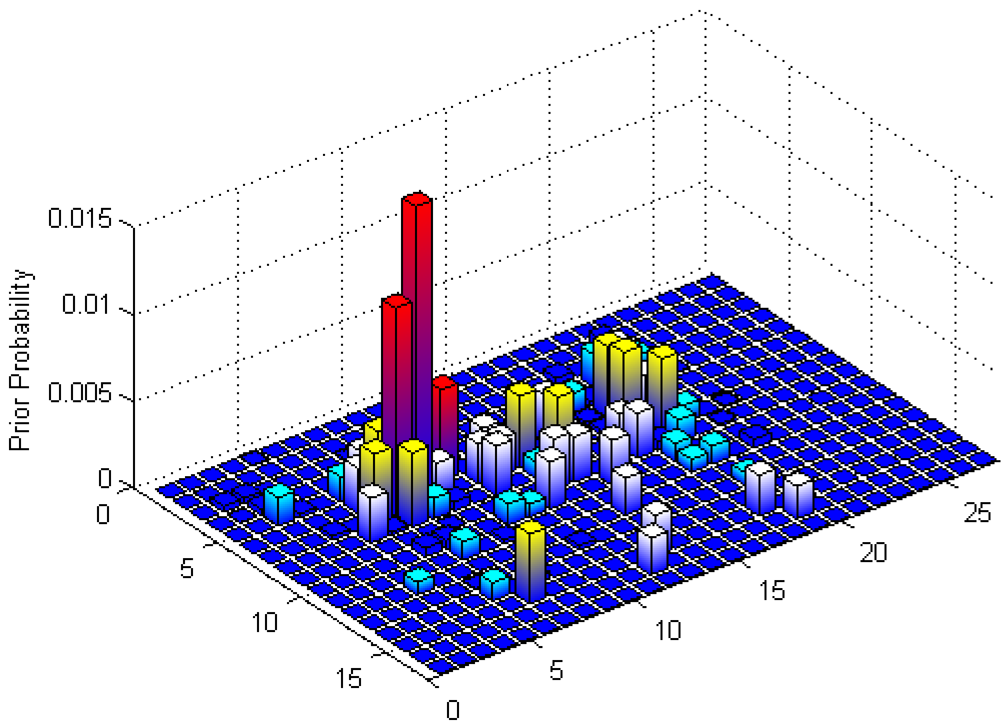

Figure 12. Prior probability map for Scene 0000 based on Gamma weighted fixations. The SALUTE report directs participants' early fixations to the target on the left. These early fixations have greater weights and results in a large mass of probability to the left of the scene.

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IV. RESULTS AND ANALYSIS

A. PREDICTING ORDER OF SUCCESSFUL ACQUISITIONS

The focus of this research is the modeling of the search process and not detection performance. It is paramount to this study that the detection probabilities are consistent for each model so that detection order and not detection performance forms the basis for comparison. The data from the 13 participant training set provides the inputs implemented by the models below. The desired outcome is not to predict the probability of detection for the test set, but to instead predict the participants' search patterns by examining the order in which participants locate targets.

1. Measures of Effectiveness (MOE)

This research is concerned with the *order* in which participants detect targets, in contrast to other studies, which consider the absolute time until each target detection. It is difficult to determine an appropriate MOE with which to compare experiment data and model data. It is not feasible to compare the actual order of detection as there are numerous possibilities for each scene. This study instead makes the comparison using two conditional probabilities of detection for each scene.

Consider a scene with five targets. If only five of 19 participants detect target one, but all five detections are the first detection for those participants, then it is important to note that the probability of detecting target one first given that it is detected is one. If the remaining 14 participants all detect target two first, the probability of detecting target two first given that it is detected is also one. It is also important to consider the probability of detecting each of the targets first given a detection in the scene. This results in a considerably higher probability of detecting target two first given a detection in the scene.

a. MOE 1

MOE 1 is the probability of detection order relative to all other targets in the scene. It is the conditional probability of detecting target *j* in order *k* given a detection in scene *m*. This probability is given by the following formula:

Pr(detecting target *j* in order *k* | a detection in scene *m*) =

$$\frac{\sum_{i=1}^{par} target\_detect_{i,j,k,m} \forall j,k,m}{\sum_{i=1}^{par} \sum_{j=1}^{target} \sum_{k=1}^{order} target\_detect_{i,j,k,m} \forall m}$$

where par *i* is the number of participants, target *j* is the number of targets in the scene, *k* is the order in which the target is detected, and *m* is the number of scenes.

Participant	Target 1	Target 2
1	0	1
2	0	0
3	0	1
4	1	2
5	0	0
6	0	1
7	1	0
8	0	1
9	0	0
10	0	0
11	0	0
12	1	0
13	0	0
14	0	1
15	1	0
16	0	0
17	0	1
18	0	1
19	0	1

Table 3. Detection order for Scene 0000 from experimental data.

Table 3 displays the order in which each participant detected each target in scene 0000. A zero indicates that the participant did not detect the target. The sum of all detections is 13. The conditional probability of detecting Target 1 first given a detection, MOE 1, is the sum of the ones in column Target 1 divided by 13 or 4 / 13 = .3076. Table 4 shows the matrix of conditional probabilities for scene 0000 where the (*i*,*j*) entry is the probability of detecting target *j* in order *i* given a detection. The zero entry in (2,1) indicates that Target 1 was never detected after Target 2.

Order	Target 1	Target 2
1	0.3076	0.6153
2	0	0.0769

Table 4. Conditional probabilities of detection for scene 0000 using MOE 1.

b. MOE 2

MOE 2 is the absolute probability of detection order for each target. It is the conditional probability of detecting target *j* in order *k* given target *j* is detected.

Pr(detecting target *j* in order *k* | target *j* is detected) =

$$\frac{\sum_{i=1}^{par} target\_detect_{i,j,k} \forall j,k}{\sum_{i=1}^{par}\sum_{k=1}^{order} target\_detect_{i,j,k} \forall j}$$

From Table 3, the sum of all detections of Target 1 is four and the sum of detections of Target 1 in Order 1 is four. This results in a conditional probability of 4 / 4 = 1.0. Table 5 is the resulting matrix of conditional probabilities for scene 0000.

Order	Target 1	Target 2
1	1	0.888889
2	0	0.111111

Table 5. Conditional probabilities of detection for scene 0000 using MOE 2.

c. Hypothesis Test

A population proportion hypothesis test based on the MOEs above determines the extent to which each model fits the experiment data. For this study, *p* is the population proportion of detections of a specified target in a given order from the population of simulated detection orders. The following test about *p* is based on a random sample of size *n*. Since *n* is small compared to the population, *X*, the number of detections based on the MOEs, has approximately a binomial distribution. Since *n* = 1000 is large, invoking the Central Limit Theorem means that *X* and the unbiased estimator $\hat{p} = X/n$ are both approximately normally distributed (Devore, 2008).

The null hypothesis is that the model proportion is equal to the human proportion. The model data is based on the training set data and the human proportion is determined by the test set data. The test procedure is constructed as follows:

$H_o : p = p_o$

$H_a : p \neq p_o$

$z = \dfrac{\hat{p} - p_o}{\sqrt{p_o(1-p_o)/n}}$ with a rejection region $z \geq z_{\alpha/2}$ or $z \leq -z_{\alpha/2}$

where *n* is the sample size, *p* is the population proportion, p_o is the sample proportion, $\hat{p}$ is the estimator of *p*, and $\alpha = \Pr(H_o$ is rejected when it is true) (Devore, 2008).

The above test is valid for $np_o \geq 10$ and $n(1-p_o) \geq 10$. Entries for which both the model and the experiment data are zero are considered as failure to reject H_o. In other words, if target *j* is never detected in order *k* in both the model data and the experiment data, then the result is a failure to reject the null hypothesis for that target. This study computes matrices similar to Tables 4 and 5 for every scene using both the experiment data and the model output. It then conducts a hypothesis test on each entry comparing the model probabilities to the corresponding experimental probabilities, which

results in a total of 128 hypothesis tests for each MOE. The proportion of entries for which the null hypothesis is rejected quantifies the results. This null hypothesis rejection rate is given by $\frac{\sum rejections}{\sum valid\_tests}$ for each MOE.

d. MOE Comparison

The two MOEs described above represent very different, but equally valuable probabilities. MOE 1 is a probability relative to all detections within a scene. This provides a comparison of each target detection against all other target detections and accounts for multiple targets detected in the same order. MOE 2 accounts only for detections of a specific target. This MOE is useful when evaluating targets individually. Table 6 is a comparison of the results from each MOE for targets for which a SALUTE report indicates a specific location. Since each SALUTE report highlights a specific target, these targets provide consistency with which to compare the MOEs. Figure 13 shows that the two MOEs lack a consistent pattern and highlights the value of considering both MOEs when comparing models.

Scene	0000	0002	0012	0020	0040	0041	0042	0043
MOE 1	1	0.947368	0.333333	0.75	0.44444	1	0	0.736842
MOE 2	0.307692	0.24	0.162162	0.054545	0.195122	1	0	0.28

Table 6. Conditional detection probabilities by MOE of targets detected first for which a SALUTE is provided.

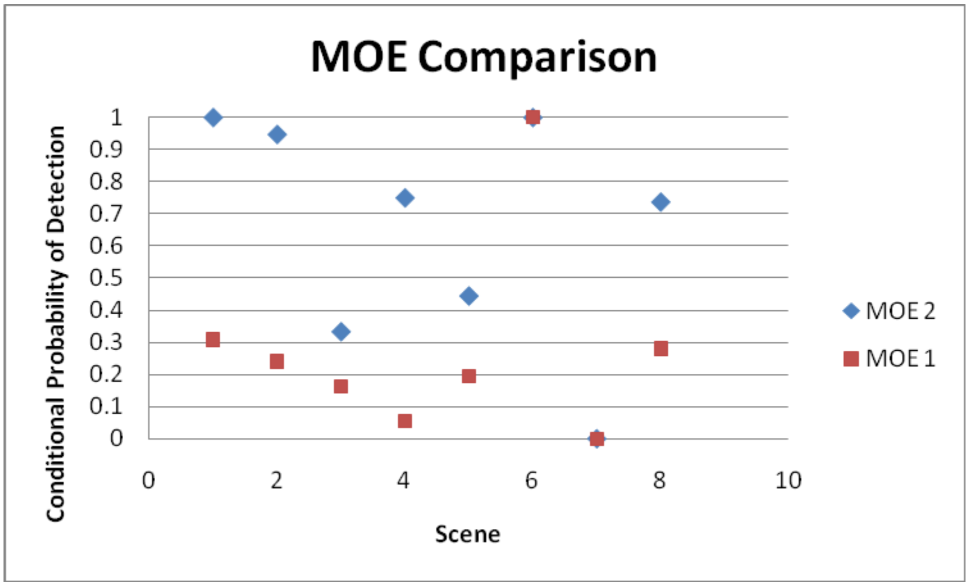

Figure 13. Comparison of MOEs using conditional detection probabilities of targets for which a SALUTE is provided.

2. Model Comparison to Current Target Acquisition Models

A windshield wiper model replicates search in current combat simulation models. This model begins on the left of the scene image and sweeps left to right and then right to left. The model uses the same predicted probabilities of detection used by the Discrete Myopic Search model when a target is encountered. The script file, which implements this model, also records the order of detection for each iteration.

Both the Discrete Myopic Search model and the windshield wiper model are run for 1000 iterations and the results are compared to the test set data at $\alpha = 0.10$, $\alpha = 0.05$, and $\alpha = 0.01$ test levels for both MOE 1 and MOE 2 where $\alpha = \Pr(H_o$ is rejected when it is true). The proportion of targets for which the null hypothesis is rejected is used to quantify the results. The hypothesis test provides evidence whether to reject the null hypothesis in favor of the alternate hypothesis or fail to reject the null hypothesis. Failing to reject the null hypothesis is not equivalent to accepting the null hypothesis, which is why this thesis uses the rejection rate to compare the models (Devore, 2008).

Tables 7 and 8 show the model null hypothesis rejection rate comparison for MOE 1 and MOE 2 respectively. These rejection rates may seem discouraging at first

glance, however, one must keep in mind both the difficulty of modeling human behavior and the vast number of combinations of target detection order. The critical result is the nearly 20% improvement using MOE 1 and 5% improvement using MOE 2 of the Discrete Myopic Search model over the windshield wiper model.

Model	α=0.10	α=0.05	α=0.01
Myopic Search	0.701	0.701	0.701
Windshield Wiper	0.8933	0.8933	0.8533

Table 7. Rejection rate comparison MOE 1.

Model	α=.10	α=.05	α=.01
Myopic Search	0.8081	0.798	0.798
Windshield Wiper	0.8556	0.8556	0.8556

Table 8. Rejection rate comparison MOE 2.

A large sample hypothesis test for two population proportions provides evidence whether the Discrete Myopic Search model rejection rate is less than the windshield wiper model rejection rate. This hypothesis test is computed using the following test procedure.

$$H_o : p_1 - p_2 = 0$$

$$H_a : p_1 - p_2 < 0$$

$$\hat{p} = \frac{X+Y}{m+n} = \frac{m}{m+n}\hat{p}_1 + \frac{n}{m+n}\hat{p}_2$$

$$z = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}\hat{q}(\frac{1}{m}+\frac{1}{n})}} \text{ with a rejection region } z \le -z_\alpha$$

where p_1 and p_2 are the population null hypothesis rejection rates of the Discrete Myopic Search and the windshield wiper models respectively, m=n=1000=sample sizes,

$\hat{p}_1$ and $\hat{p}_2$ are the estimators of p_1 and p_2, $\hat{p}$ is the estimator of the population rejection rate, and $\hat{q} = 1 - \hat{p}$ (Devore, 2008).

	α=.10	α=.05	α=.01
MOE 1	-10.6932	-10.6932	-8.1832
MOE 2	-2.8399	-3.4035	-3.4035
$-z_\alpha$	-1.28	-1.645	-2.575

Table 9. Test statistics for model comparison by MOE.

Table 9 shows that the *z* statistics result in a rejection of the null hypothesis in favor of the alternative for each α test level for both MOEs. Furthermore, the *p-value* is negligible for each MOE 1 *z* statistic and the largest *p-value* for MOE 2 is .0019. The *p-value* is the smallest level of significance at which H_o would be rejected and = $\Phi(z)$ for a lower tailed test (Devore, 2008). In other words, a *p-value* $\leq \alpha$ means reject the null hypothesis at test level α. This gives strong indication that the rejection rate of the Discrete Myopic Search model is less than the windshield wiper model for both MOEs. In other words, the Discrete Myopic Search model fails to reject the null hypothesis on more occasions of detection order than the windshield wiper model. This indicates that the Discrete Myopic Search model is more realistic when compared to the human experimental data than the windshield wiper model.

B. VALUE OF INFORMATION

It is clear that contextual information changes the search behavior of the participant, but it is very difficult to interpret the value of such information for this experiment. The measure of effectiveness to determine the value of information is the probability of detection from the participant data. The probability of detection is compared on targets for which the experiment provides a SALUTE with those targets that do not have a SALUTE. This comparison is difficult to make because the scenes with SALUTE reports are different than scenes without SALUTE reports. This thesis addresses this limitation by investigating the effect of target size and the number of

targets in a scene on the probability of detection. It does not address other less quantifiable factors such as the amount of clutter. Additional limitations on the detection probability comparison include certain confounding factors such as learning, fatigue, and a difference in the number of targets in a SALUTE scene versus a scene with no SALUTE. Although these factors were considered during the design of the experiment, this research does not isolate each factor to make an objective assessment on the affect of information on the probability of detection. The initial findings within this section, although interesting, are not conclusive and provide a foundation for future research. APPENDIX A contains all scene images for a qualitative comparison of scenes with and without SALUTE reports.

1. Effect of SALUTE Report on Probability of Detection

One may expect that the probability of detection is greater on a target for which a SALUTE report exists; however, the following analysis shows a different result from experimental data. The probability of detection for targets for which a SALUTE report provides information is 0.5855. The probability of detection for targets for which there is no SALUTE report is 0.7616. There are m = 608 opportunities to detect a target with no SALUTE and n = 152 opportunities to detect a target with a SALUTE report. Again invoking the Central Limit Theorem, a large sample population proportion hypothesis test, similar to the one described in the previous section, provides evidence that the probability of detection of targets without a SALUTE is greater than that of targets with a SALUTE.

$$H_o : p_1 - p_2 = 0$$

$$H_a : p_1 - p_2 < 0$$

with a rejection region $z \geq z_\alpha$

where p_1 is the proportion with SALUTE and p_2 is the proportion without SALUTE (Devore, 2008).

The test statistic z = 6.0393 is greater than z_α for $\alpha = 0.10$, 0.05, and 0.01 indicating that the null hypothesis is rejected in favor of the alternative hypothesis. A *p-value* < .0002 further strengthens this test. Participants appear to perform better on targets with no SALUTE report. These results are interesting considering that each SALUTE report refers to a single specific target in the scene. Even more interesting is the fact that 142 out of 152 or 93.42% of the first five fixations occur in the vicinity of the target referred to by a SALUTE. This result also leads to the question whether the SALUTE report affects the overall probability in a scene.

The probability of detection for all targets in a scene in which a SALUTE report is given is 0.7025. The probability of detection for all targets in a scene in which no SALUTE report is given is 0.7307. There are *m* = 323 opportunities to detect a target in a scene with no SALUTE and *n* = 437 opportunities to detect a target in a scene with a SALUTE report. The large sample population proportion hypothesis test described above is again the method to determine whether these probabilities are equal. The *p-value* for a two-tailed test = $2\left[1-\Phi\left(|z|\right)\right]$ (Devore, 2008).

$$H_o : p_1 - p_2 = 0$$

$$H_a : p_1 - p_2 \neq 0$$

with a rejection region $z \geq z_{\alpha/2}$ or $z \leq -z_{\alpha/2}$ (Devore, 2008).

The test statistic z = 0.7832 falls outside the rejection region for α =0.10, 0.05 and 0.01, which indicates a failure to reject the null hypothesis. A *p-value* of .4354 re-enforces this conclusion. This means that there is not enough evidence to say that the probability of detection in a scene with SALUTE is different than that in a scene with no SALUTE.

The discrepancy in detection probabilities for targets with and without a SALUTE is difficult to quantify. One possible explanation could be target size. The average size in pixels of a SALUTE target is 189 pixels and the average with no SALUTE is 149 pixels. This shows that the discrepancy in detection probabilities is not due to the size of the target. Figure 14 highlights the fact that target size has no significant impact on the

probability of detection since there is no distinguishable pattern with or without a SALUTE. One may expect an increase in detection probability as the target size increases, however the proportion of detections above 0.90 is higher for targets less than 200 pixels compared to the same proportion for targets greater than 200 pixels.

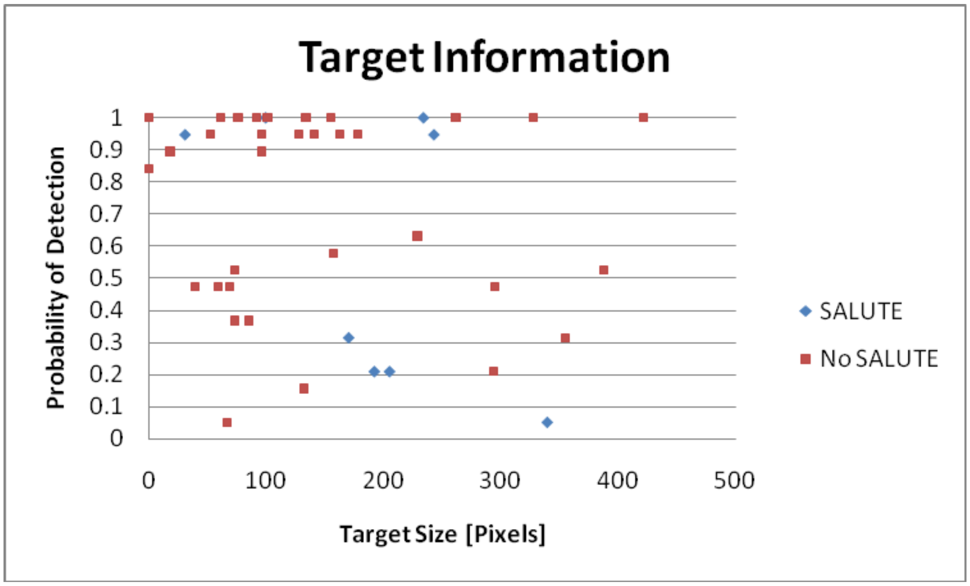

Figure 14. Probability of detection for targets with and without SALUTE report.

Tables 10 and 11 show the average number of detections and the conditional probability of detection given the number of targets in a scene with and without a SALUTE report. Figure 15 shows that participants perform slightly better in scenes with two and three targets when a SALUTE is provided and significantly worse in scenes with four targets.

Number Targets	Frequency of Scenes	Total Detections	Average Detections per Scene	Probability of Detection
0	0	0	0	0
1	1	6	0.3157	0.3333
2	2	50	1.3157	0.6578
3	3	121	2.1228	0.7076
4	1	55	2.8947	0.7236
5	1	75	3.9473	0.7894

Table 10. Detection statistics for scenes with SALUTE report.

Number Targets	Frequency of Scenes	Total Detections	Average Detections per Scene	Probability of Detection
0	2	0	0	0
1	0	0	0	0
2	2	49	1.2894	0.6447
3	3	112	1.9649	0.6549
4	1	75	3.9473	0.9868
5	0	0	0	0

Table 11. Detection statistics for scenes without SALUTE report.

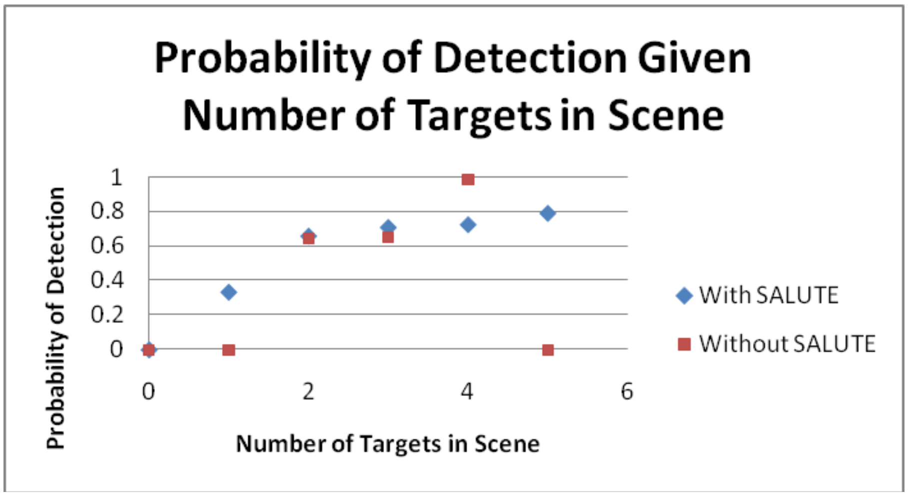

Figure 15. Detection probabilities for scenes with and without SALUTE report.

2. Effect of SALUTE Report on Detection Order

Figures 16 through 31 display the eight scenes for which a SALUTE report is given followed by a comparison of the first detection probability, MOE 1, for each model and the experiment data. The blue bar is the experiment data, the green bar is the Discrete Myopic Search model, and the red bar is the windshield wiper model. Targets are highlighted in red for the benefit of the reader. The SALUTE report is written in white at the bottom of the scene. Keep in mind that the SALUTE report in the experiment is a verbal report that occurs prior to scene exposure. The probability of detection from the experimental data is in white writing in parentheses near each target. Moving targets are highlighted with a white arrow.

In six of eight scenes, the SALUTE target is detected first given a detection, MOE 1, with the highest probability for the Discrete Myopic search model. This occurs because the model is based on weighted fixations and 93.42% of the time one of the first five fixations occur within one degree of the SALUTE target. In only three of eight scenes the SALUTE target has the highest MOE 1 first detection probability for the experiment data. MOE 2 indicates that the SALUTE target is detected first given that it is detected 66.29% on the time. The first detection order for the experiment data is greatly affected by the low probability of detection for the SALUTE targets. The windshield wiper model only provides the highest MOE 1 first detection probability to the SALUTE target in two of eight scenes. It is important to note that all models have the correct first order detection probability for scene 0041 because there is only one target, although the probability of detection is very low at 0.3158.

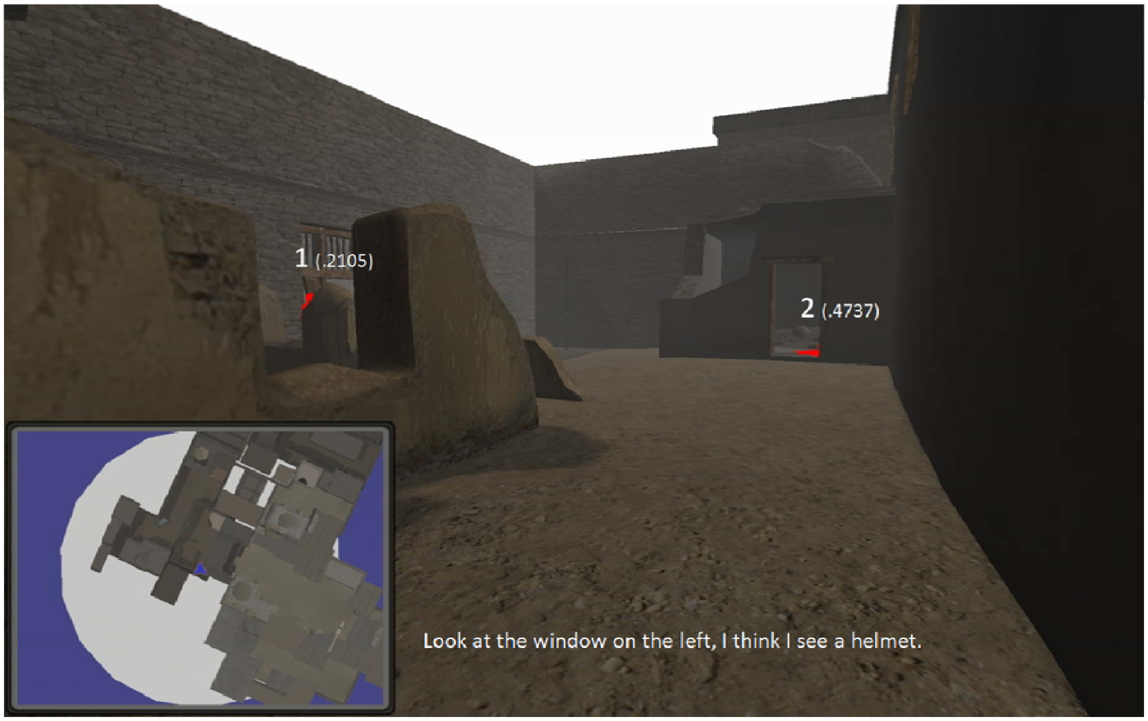

Figure 16. Scene 0000 with SALUTE and detection probabilities.

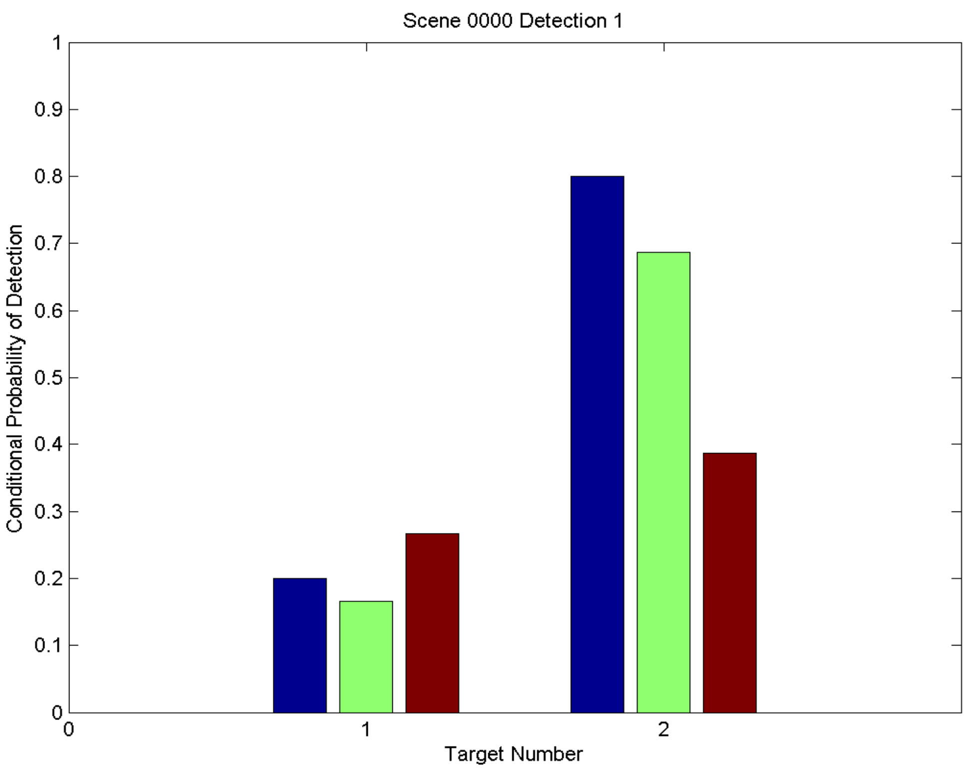

Figure 17. Scene 0000 first detection model comparison.

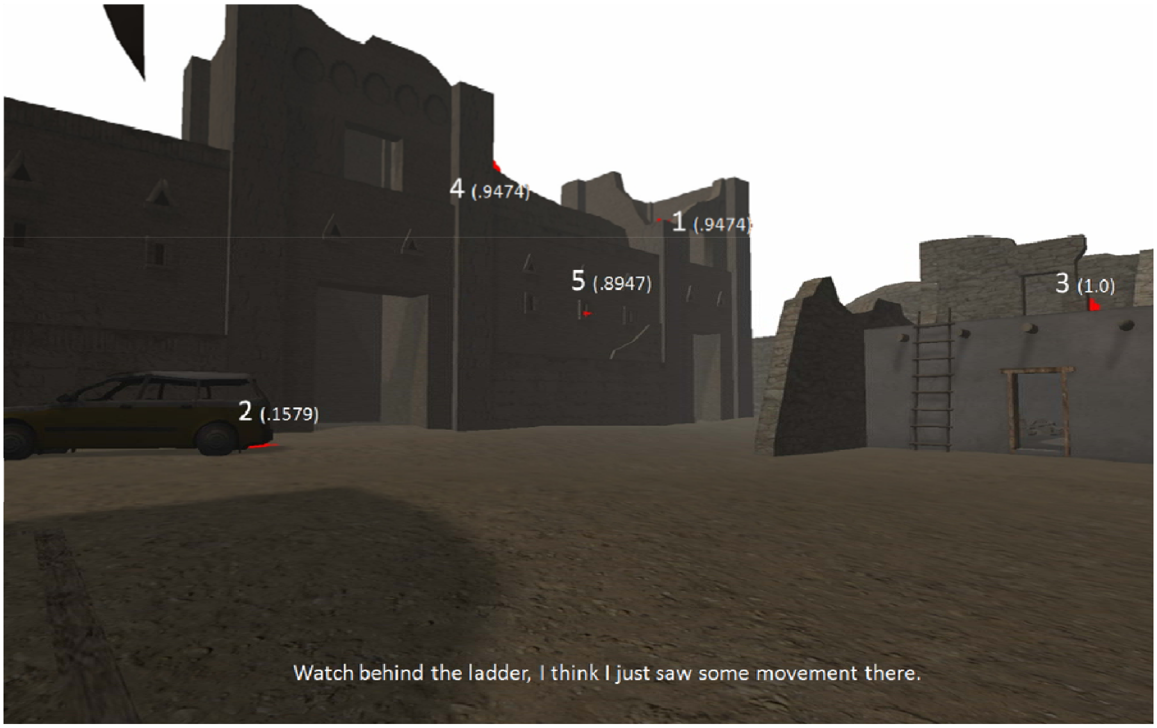

Figure 18. Scene 0002 with SALUTE and detection probabilities.

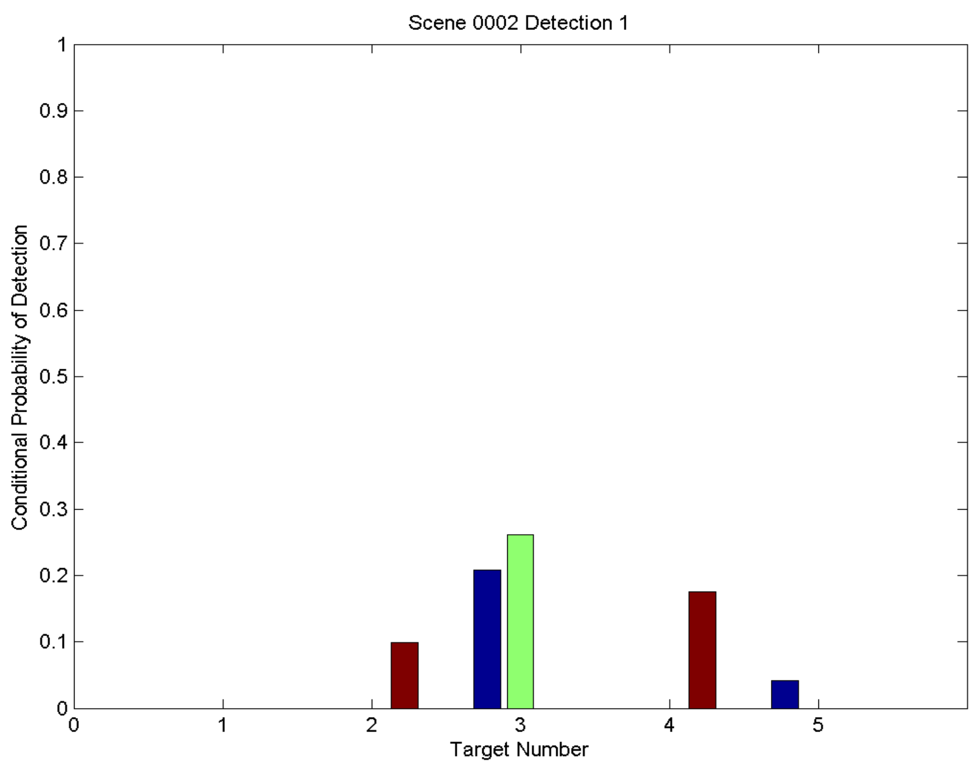

Figure 19. Scene 0002 first detection model comparison.

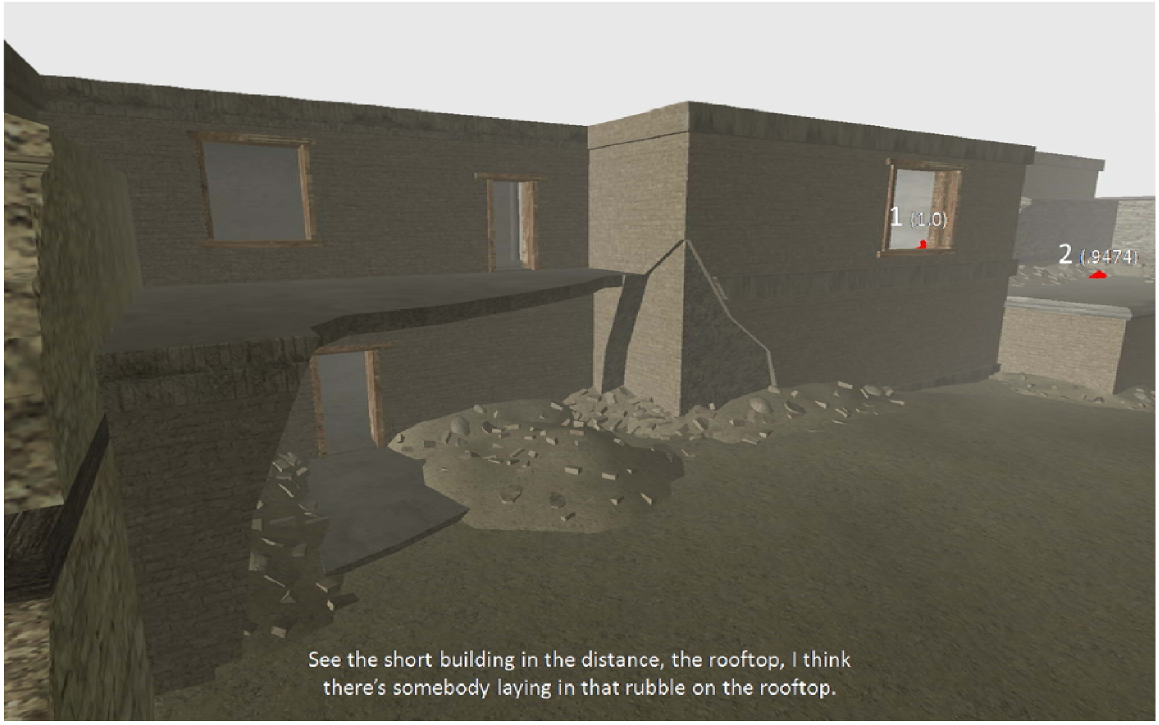

Figure 20. Scene 0012 with SALUTE and detection probabilities.

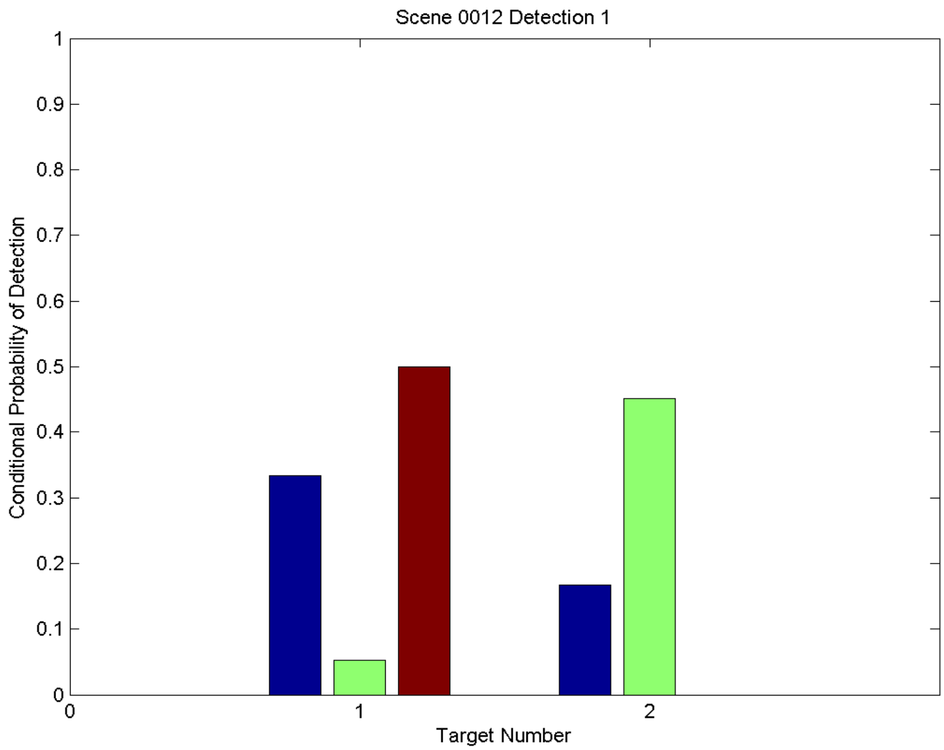

Figure 21. Scene 0012 first detection model comparison.

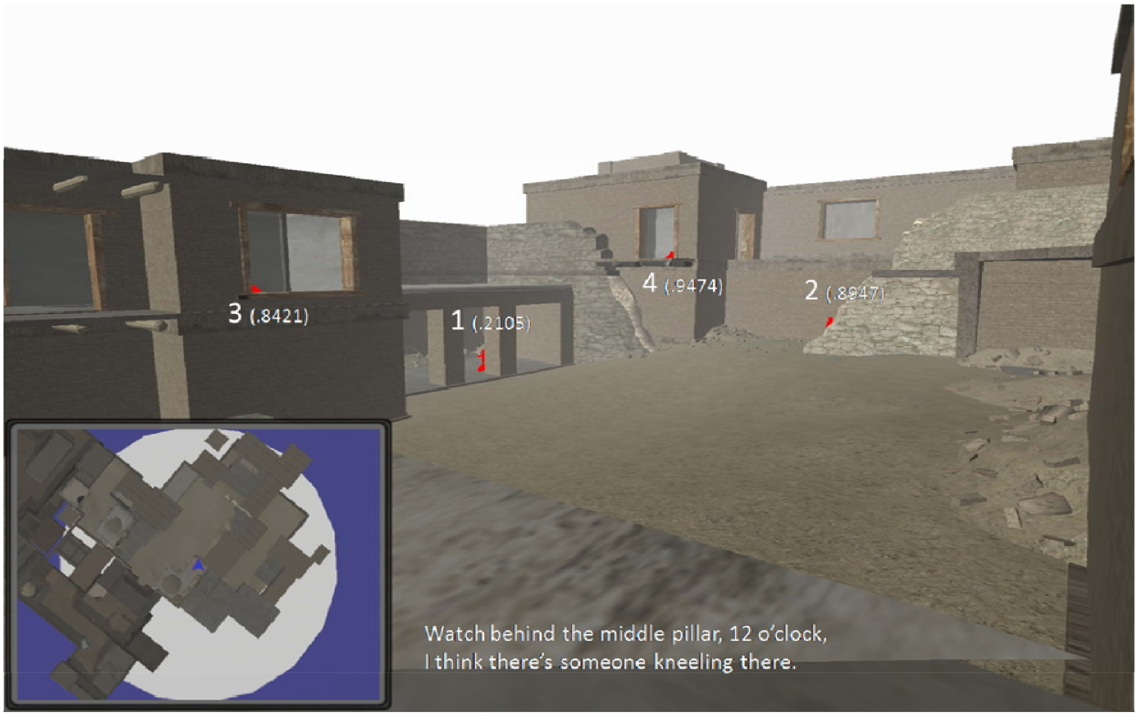

Figure 22. Scene 0020 with SALUTE and detection probabilities.

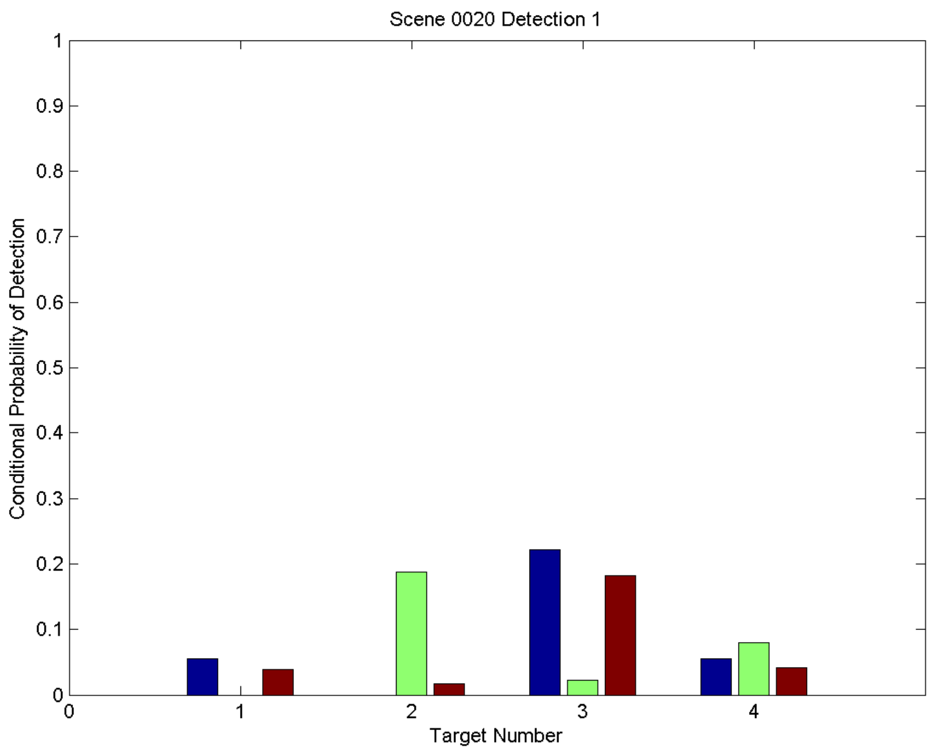

Figure 23. Scene 0020 first detection model comparison.

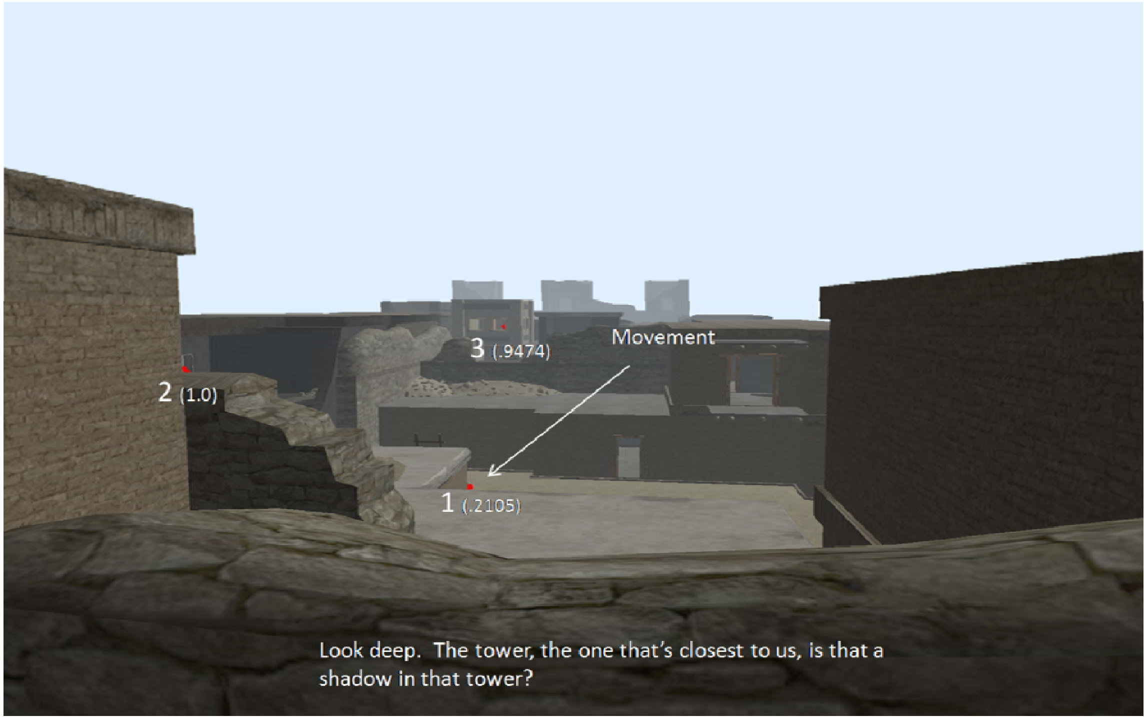

Figure 24. Scene 0040 with SALUTE and detection probabilities.

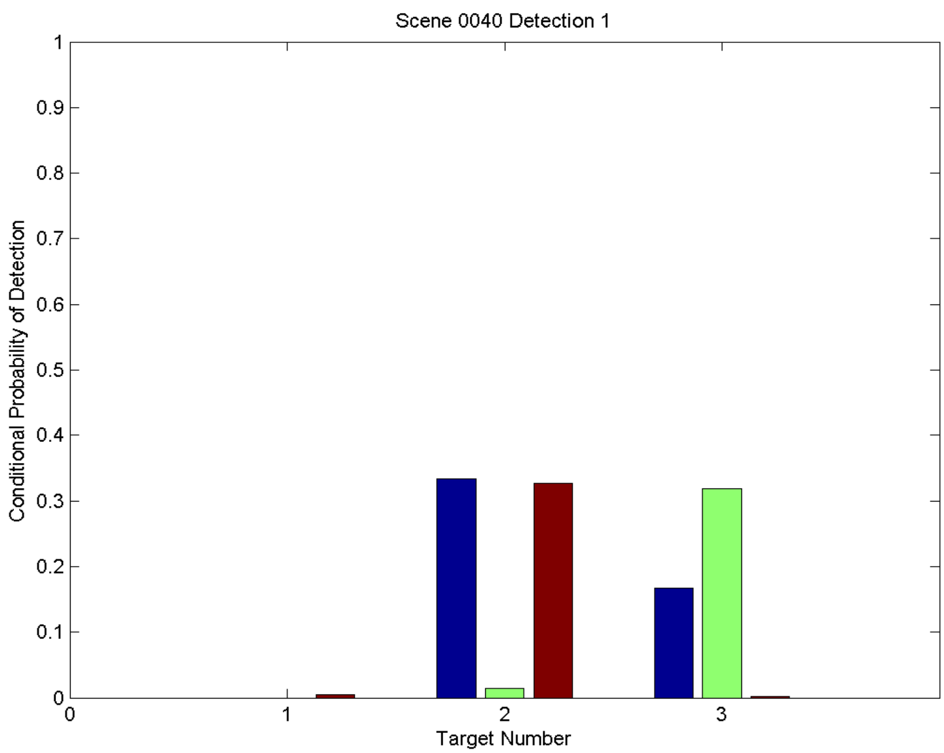

Figure 25. Scene 0040 first detection model comparison.

Figure 26. Scene 0041 with SALUTE and detection probabilities.

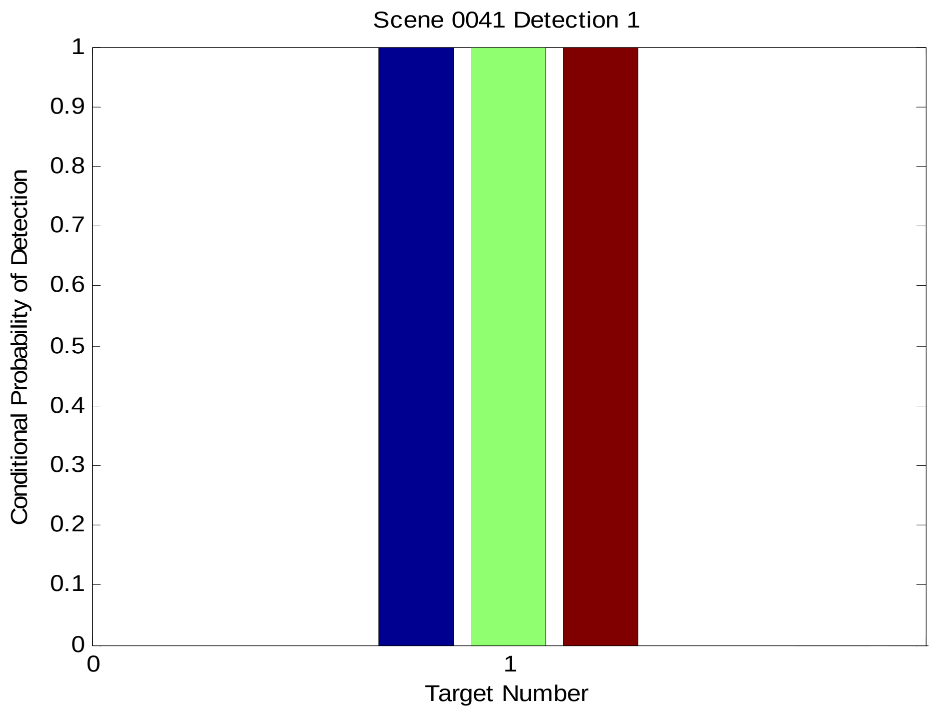

Figure 27. Scene 0041 first detection model comparison. All detections occur first because there is only one target in this scene.

Figure 28. Scene 0042 with SALUTE and detection probabilities.

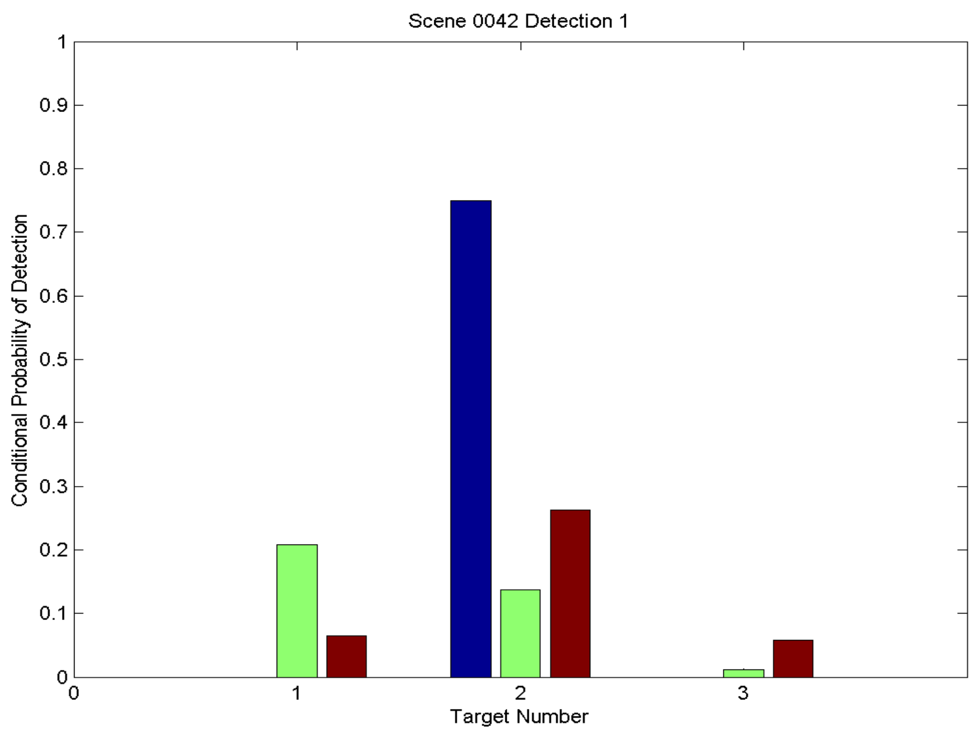

Figure 29. Scene 0042 first detection model comparison.

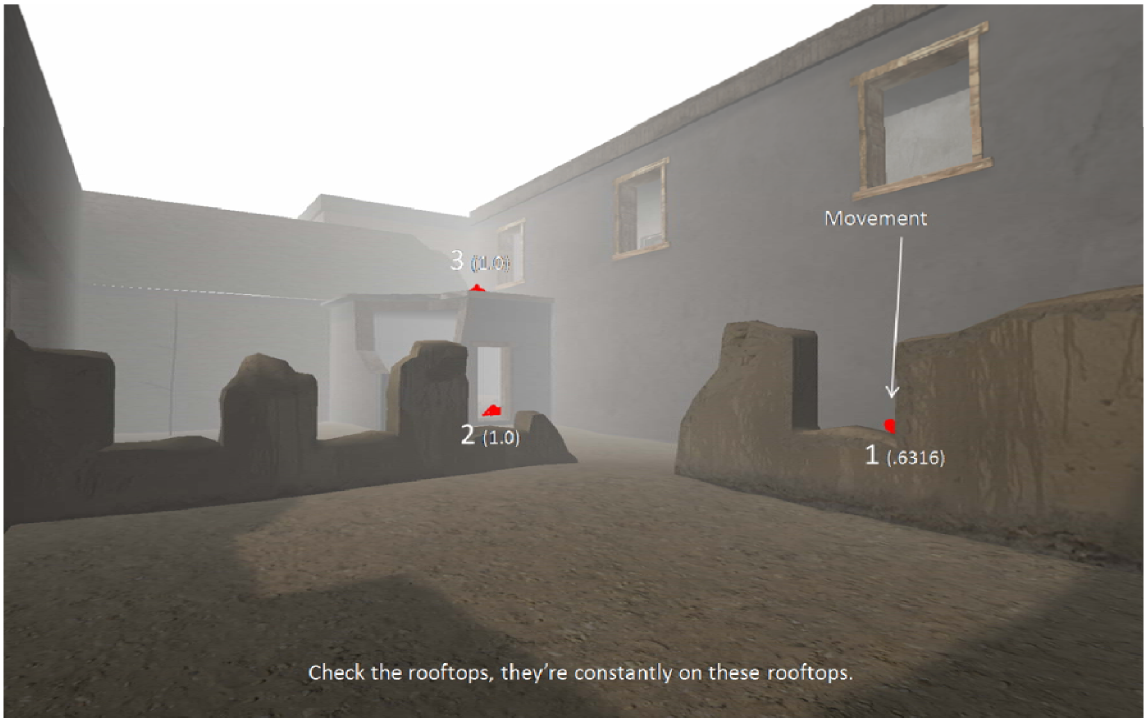

Figure 30. Scene 0043 with SALUTE and detection probabilities.

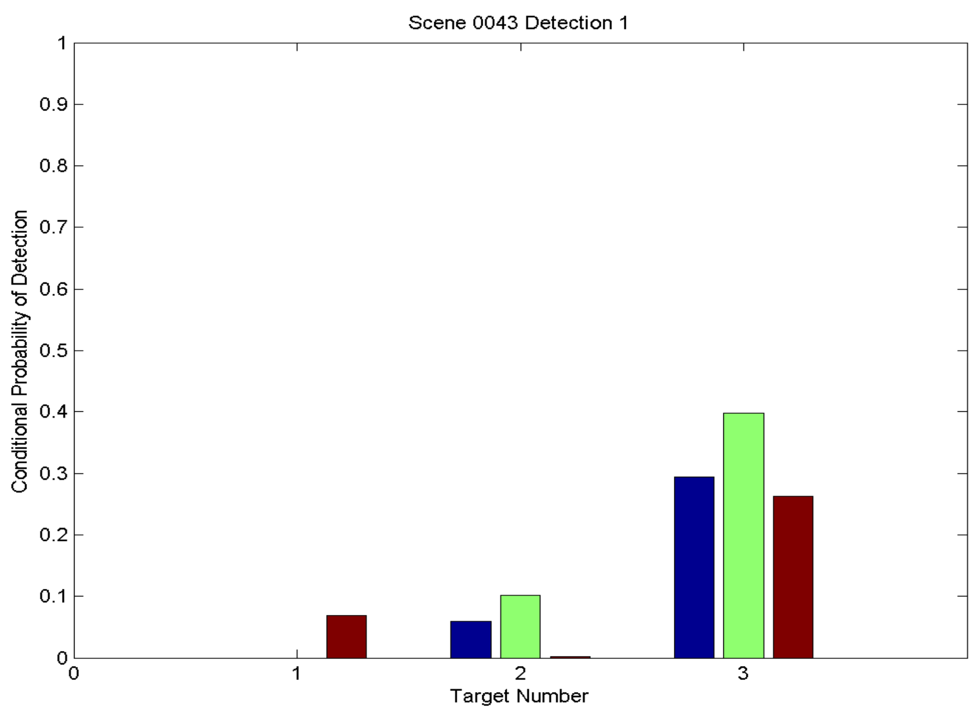

Figure 31. Scene 0043 first detection model comparison.

3. Effect of SALUTE Report on Search Pattern

The previous sections showed statistically how the search technique implemented by current combat models is not representative of human search. This section seeks to show qualitatively how human participants neither search scenes randomly nor do they waste search effort in areas where targets are not likely to exist. It also shows how a SALUTE report affects the search behavior of the participants, as well as the Discrete Myopic Search model.

The SALUTE dictates the initial fixations just as it drives the detection order in the Discrete Myopic Search model. As noted in the previous section, participants fixate one of the first five fixations in the vicinity of a SALUTE target with probability .9342. These weighted fixations result in the selection of the SALUTE target as the first location to search by the Discrete Myopic Search model. This is also highlighted in the previous section where the highest first detection probability, MOE 1, occurs at the SALUTE target location in six of eight scenes for the Discrete Myopic Search model. Figures 32 and 33 demonstrate how the model incorporates the additional information provided by the SALUTE report. Figure 32 is a prior probability map based only on the number of fixations in each cell. This representation shows very similar probabilities associated with the window and the door in the scene (See Appendix A, Scene 0000). In contrast, Figure 33 is the prior probability map based on weighted fixations. The earlier fixations carry more weight, which reflects the fact that participants follow the SALUTE report information to the window first.

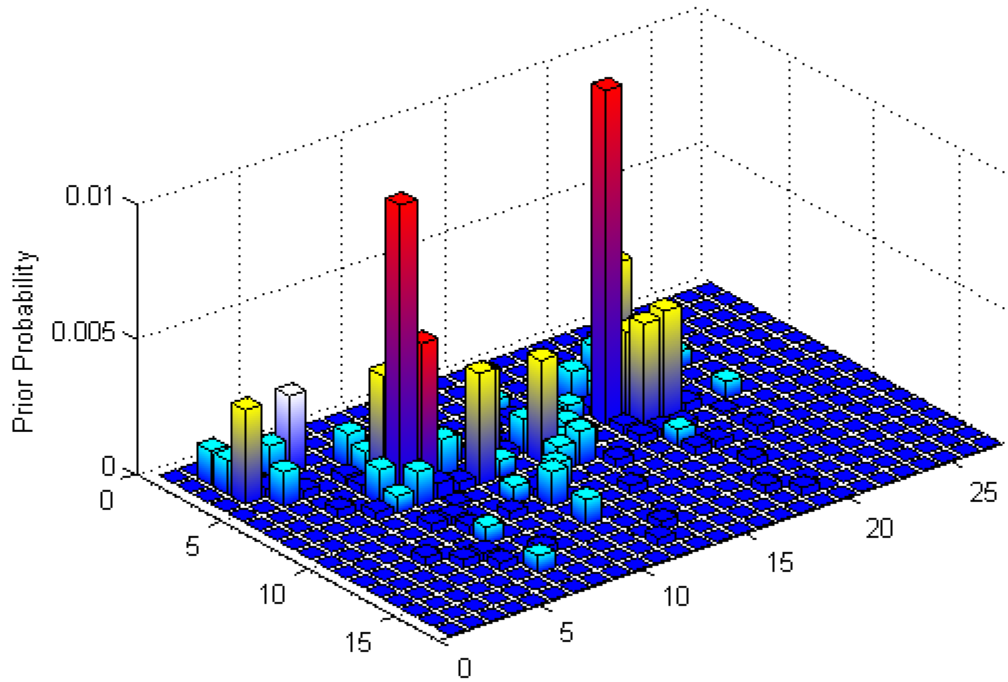

Figure 32. Scene 0000 prior based on number of fixations per cell.

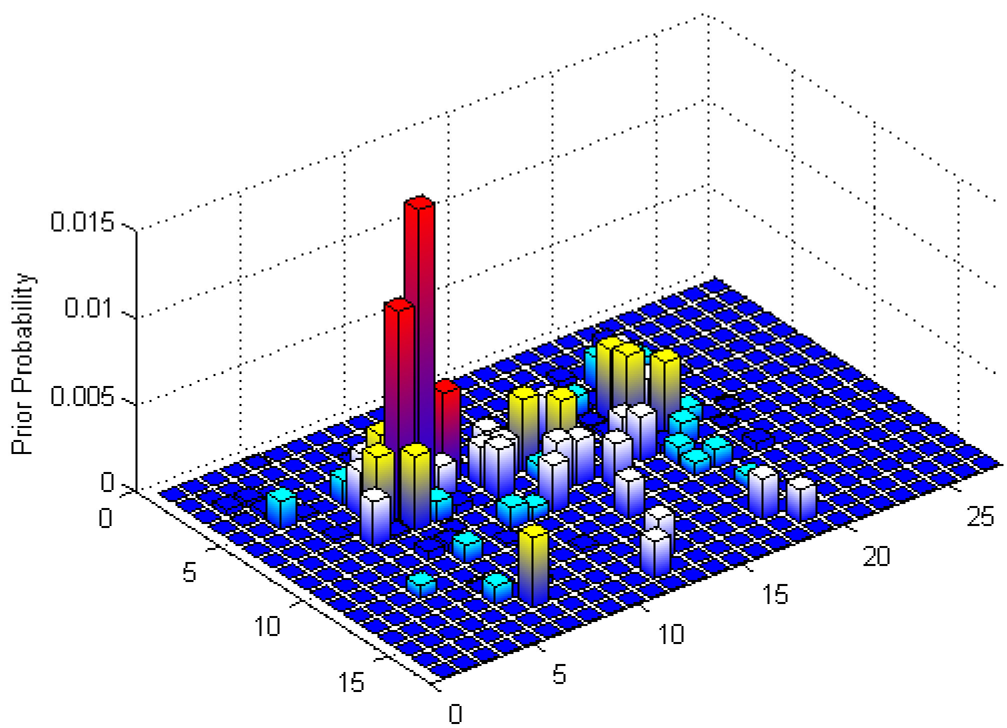

Figure 33. Scene 0000 prior based on Gamma weighted fixations highlights the effect of a SALUTE report on the probability distribution.

Figures 34 to 37 show the progression of fixations one through four for all 19 participants on a scene with no SALUTE report. One must keep in mind that the first fixation occurs in the center of the scene as the participants are shown a blank wall prior to the scene. One may note that there is no single pattern followed by all participants. It is also important to note that, although there is not one pattern, the fixations all occur at common relevant points.

In the scenes in which no SALUTE is reported (See Figures 34 to 37), each participant arrives at each target in his own pattern. Fixations occur along edges such as the walls, in the rubble, and around the window in the top left. Despite no common pattern, each participant quickly closes on one of the targets within the first four fixations. Participants waste no search effort scanning from left to right or from front to back of the scene. This demonstrates the lack of a systematic windshield wiper patter and suggests that the search pattern is a function of the environment.

Figures 38 to 41 show a contrast in the search pattern caused by the SALUTE report. The SALUTE report for this scene is “Look at the window on the left, I think I see a helmet.” The SALUTE clearly directs the attention of the participants to the target in the window. Three participants shift attention to the target in the door by the third fixation. This occurs because some participants visually move more quickly through the scene. It is pertinent to note that once again the search patterns do not waste search effort.

Figure 34. First fixations no SALUTE

Figure 35. Second fixations no SALUTE

Figure 36. Third fixations no SALUTE

Figure 37. Fourth fixations no SALUTE

Figure 38. First fixation with SALUTE.

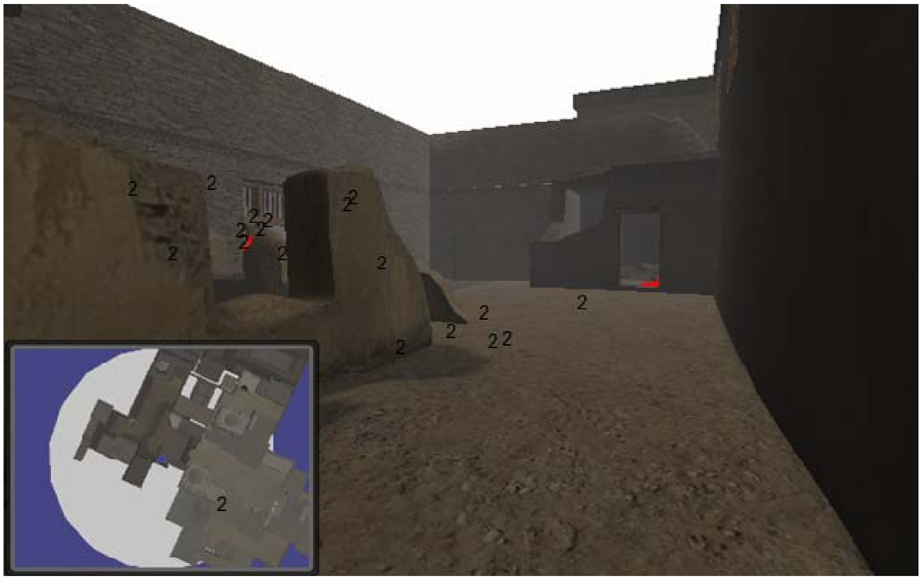

Figure 39. Second fixation with SALUTE.

Figure 40. Third fixation with SALUTE.

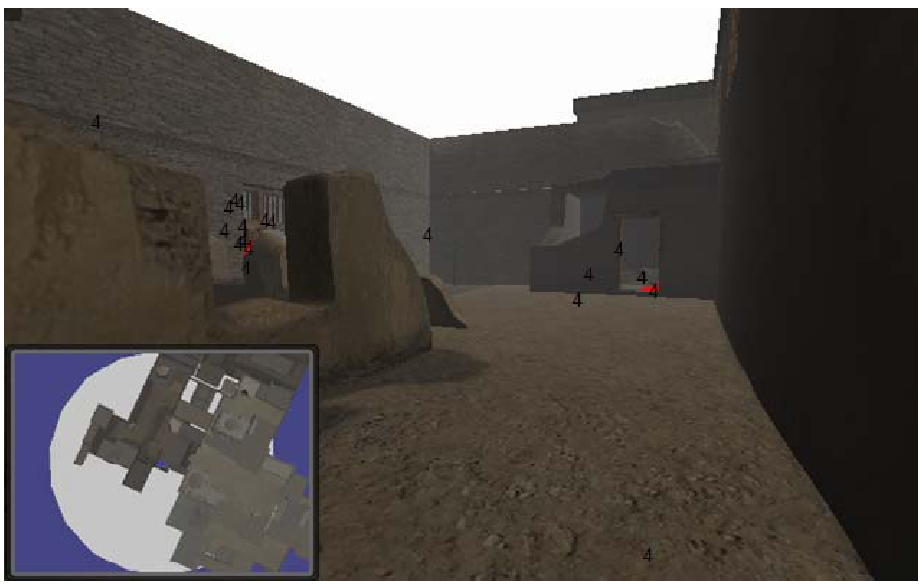

Figure 41. Fourth fixation with SALUTE.

V. CONCLUSIONS AND RECOMMENDATIONS

This thesis uses experimental search data to develop a realistic, statistically based, search model to mimic human search behavior. Careful analysis of eye-tracking and user input data results in accurate fixation determination and detection probabilities, which form the basis for a quantitative application of search theory. These data serve as inputs to a visual search application of a Myopic Search model with discrete looks. Each cell in a discretized image contains a probability that a target is present in that cell based on fixation data. Basing the probabilities on experimental fixation data carries the underlying assumption that a human participant will prioritize his gaze order based on where he believes a target is most likely to be present. The Discrete Myopic Search model chooses the cell with the highest probability for each discrete look. This application results in the optimal allocation of discrete search effort and closely follows the search patterns of human participants.

The thesis continues by investigating the effect of contextual information on the search behavior of human participants. Contextual information is in the form of a verbal SALUTE, which provides information on the location of a specific target in the scene. This information clearly affects search behavior as one of the first five fixations occur within one degree of the target highlighted by the SALUTE in 93.42% of the experimental participant data. Interestingly, the probability of detecting these targets tends to be lower than that of targets for which no SALUTE is given despite similarities in target and scene characteristics.

A. COMBAT MODELS

Current combat simulation models implement a windshield wiper search pattern that is unnaturally systematic and does not account for locations that are more likely to contain targets. This results in search behavior that is inconsistent with human participant data and wasted search effort. Regardless of the size of the FOR or the FOVs contained within the FOR, a windshield wiper search pattern is not representative of human search behavior. This thesis develops a replication of this windshield wiper

search behavior and compares it with the proposed Discrete Myopic Search model. Hypothesis testing reveals a significant improvement in search performance of the Discrete Myopic Search model over the windshield wiper model. This improvement is quantified by comparing the order in which targets are detected by each model to the order in which participants detected the targets.

A soldier is never responsible for searching a large FOR, rather, he is responsible only for a small FOV (U.S. Army, 2007). Combat simulation models should not require individual entities to search a large FOR and the entities should consider only locations in which a target may be located when searching a smaller FOV. This additional consideration can occur through the design of the terrain and the location of individual entities in relation to the terrain. The simulation can assign probabilities to locations likely to contain a target such as doors, windows, roof tops, and behind objects in the terrain.

Contextual information clearly plays a key role in not only the search behavior of individuals, but also the probability of detection. It is common practice for soldiers to share information on known or suspected enemy locations. Simulation models should have a means of passing information among entities in close proximity. If one entity sees a target, that entity should share that information with other entities in the team or squad and each entity should act accordingly.

B. URBAN SEARCH IN ARMY DOCTRINE

U.S. Army doctrine does not propose search techniques for urban terrain. This research shows that human participants with military training and urban combat experience choose specific locations to search for enemy personnel. These search patterns are not consistent with the rural search techniques proposed in the Army doctrine described in Chapter I. This thesis does not fully investigate the effectiveness of the search patterns of the participants, however, the level of expertise of the participants provides a qualitative indication of effective search performance. The following language is based on experimental search patterns and is recommended for further investigation for possible future implementation in Army doctrine.

> The complex nature of unnatural urban terrain provides a three dimensional search problem, which requires a more deliberate search process. The curvature of the human form is unique to the straight lines found in the modern urban environment. The soldier should always address the most immediate threat first. He should begin with a rapid scan of the scene using peripheral vision to find human figures and movement. A more deliberate search begins with objects nearest to the soldier. The soldier should focus on any object which may provide cover and or concealment for enemy personnel. Carefully search objects such as, but not limited to, automobiles, piles of rubble or trash, signs, barrels, and trash cans. Pay special attention to edges and corners of buildings to include windows, doors and roof tops.

C. AREAS OF FUTURE RESEARCH

The experiment conducted by TRAC Monterey was a two-tier experiment. The first tier produced the data for this research and included a three dimensional, first person shooter style portion in which participants navigate through a virtual urban environment in search of stationary targets. This portion of the experiment collected the same data including mouse clicks and eye tracking data. This study did not incorporate any of these data as they pose different challenges and, potentially, deeper insight into the search problem.

Tier 2 of the experiment took place at Fort Benning, GA with a virtual environment and fully equipped soldiers. The soldiers used actual weapons to indicate detections and wore a head mounted eye tracking device. These data can be analyzed to advance the findings in this thesis.

Future search and target acquisition research should incorporate multiple participants working together, each with his own assigned sector of responsibility. Soldiers never operate alone. This dynamic may provide key insight into the way soldiers search when working as a member of a team or squad. It may also provide a realistic avenue to study the effect of additional situational awareness as soldiers pass information among one another.

This thesis implements a statistical approach to model human search behavior and does not investigate the characteristics of fixations. This research may be extended by investigating why certain objects draw attention. Experimental data shows that participants tend to fixate on windows, doorways, along roof tops, and along the sides of buildings. Each of these urban features incorporates straight lines and corners. Human figures consist of curvature around the head and shoulders, which is in sharp contrast to the straight lines found in an urban environment. Future research may investigate a model which searches along edges to find curvature. Additional research may consider the visual contrast between a human and the urban background. Combining the curvature and contrast of an object may be sufficient to identify the object as a human. Further research is required to distinguish a hostile target from a non-combatant.

This research uses target detection order as a means to compare search patterns constructed by two models. This comparison relies on detection probabilities to develop a corresponding search pattern and implements hypothesis testing to quantify the results. Although fixations form the foundation of the Discrete Myopic Search model, which constructs a search pattern, this thesis does not directly evaluate the fixations. Future research may implement a non-parametric assessment of fixation locations. Comparing fixation locations and ordering may provide a deeper insight into the human visual search process.

There is a clear distinction between search in rural terrain versus search in urban terrain, which is not discussed in current Army doctrine. The purpose of this thesis is to model human search performance, not to identify the most effective search strategy. Additional research is necessary to compare search strategies to determine one that is most effective in an urban environment. Such research may consider first the effectiveness of search, based on detection performance. This research may consider proportion of detections, number of false detections, and mean time to detection as measures of search performance. One may then determine the most effective search performance and then evaluate the search patterns.

This thesis investigates the role of additional situational awareness on search behavior and detection performance. The experimental data provide a clear indication that such contextual information drives participants' initial fixations. It also demonstrates that this information may serve as a distraction as the detection performance decreases when a SALUTE is provided. Although the results of this study are not conclusive regarding the role of information in the STA process, it provides a rich avenue for future research.

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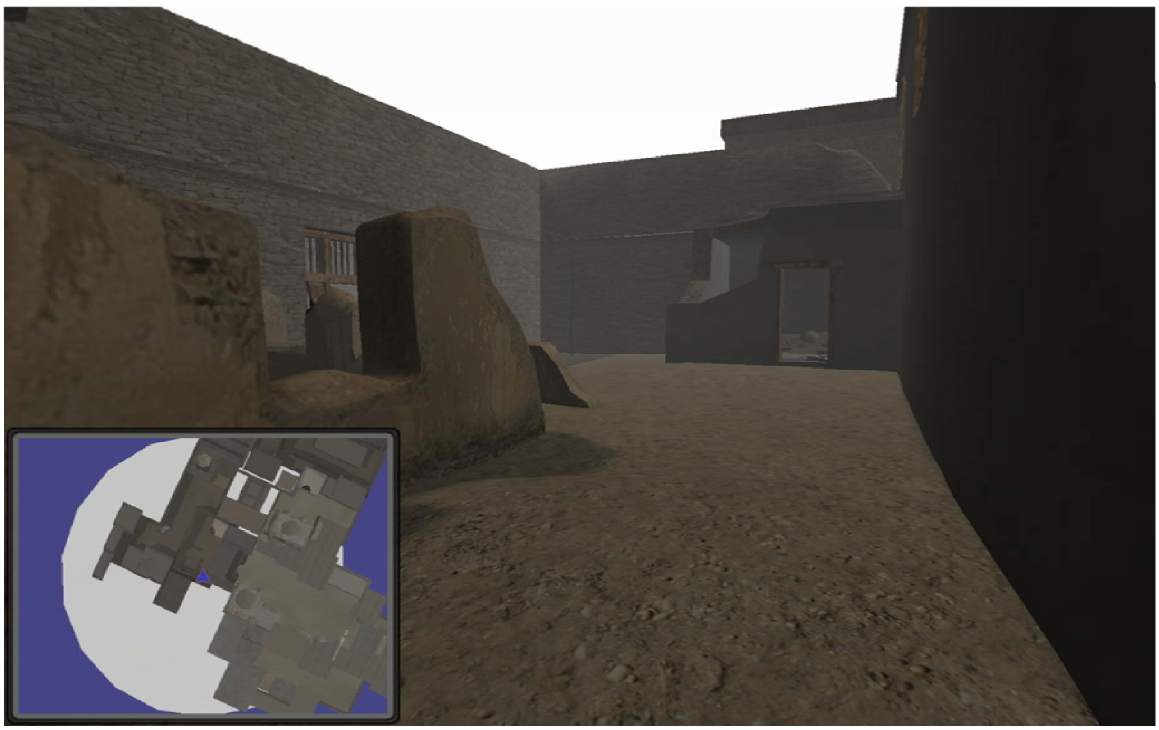
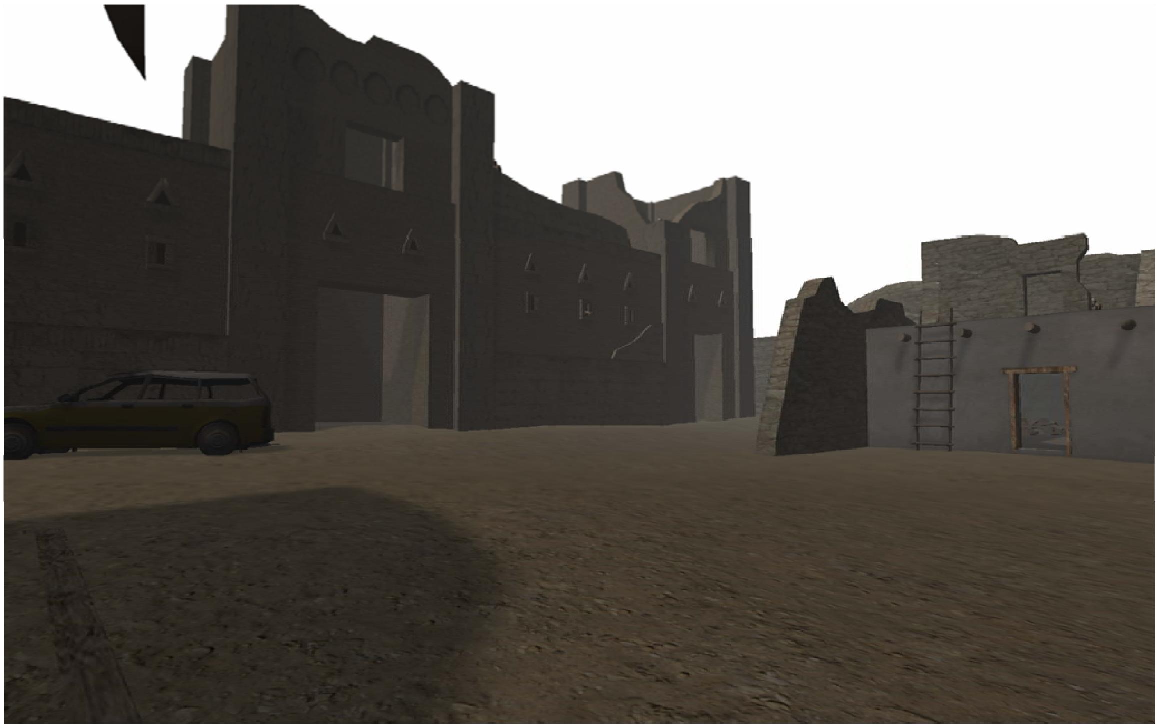
APPENDIX A SCENE IMAGES

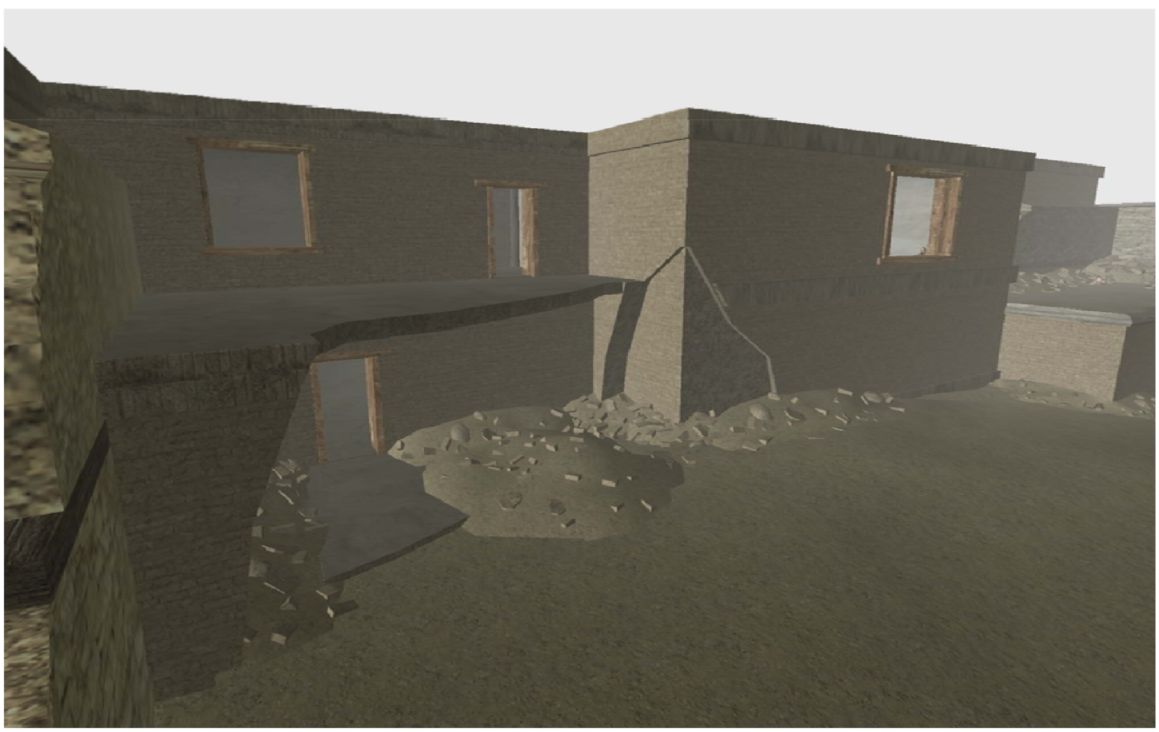
This appendix contains the unaltered scenes from tier 1 of the SA/STA experiment. There are a total of 16 scenes and the number of targets in each scene ranges from zero to five. Scene presentation is random for each participant. Targets may be completely exposed or partially occluded, standing, kneeling, or lying in the prone position. Eight scenes have movement, eight have SITREPS, eight have SALUTE reports, and eight have Mini-Maps. Chapter II Section A. 3. of this thesis describes the scene variations in greater detail. These images, as well as images in which the targets are highlighted in red, are available at http://faculty.nps.edu/thchung/VisualSearch/scenes/.



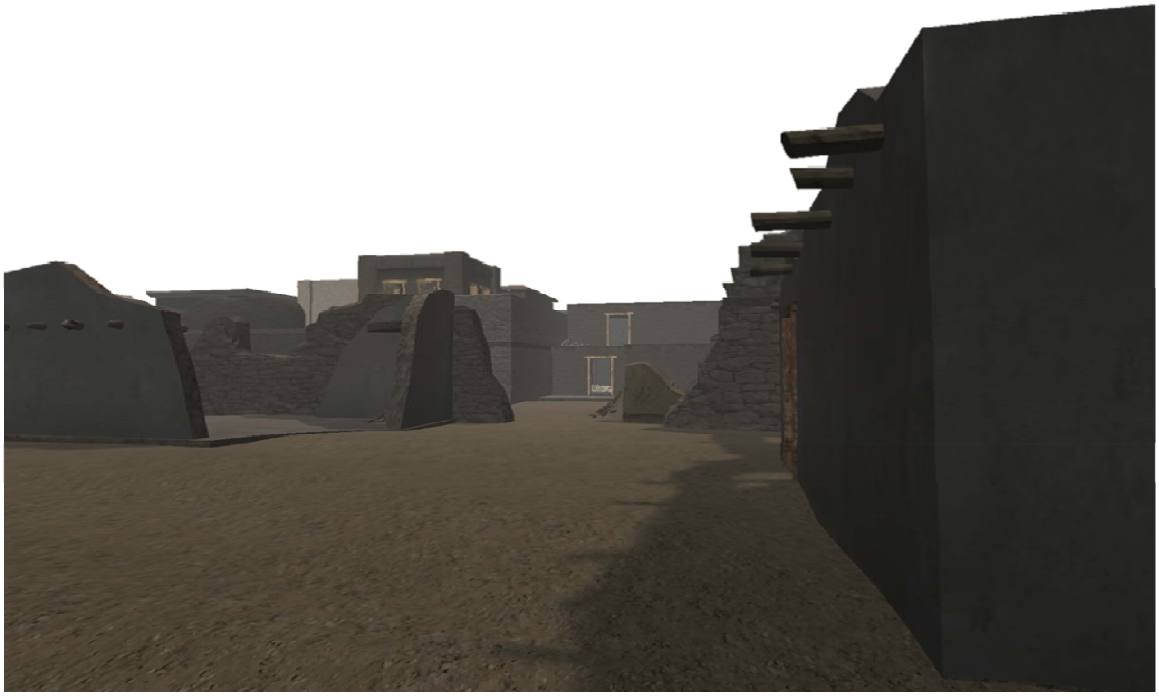
Scene 0000.



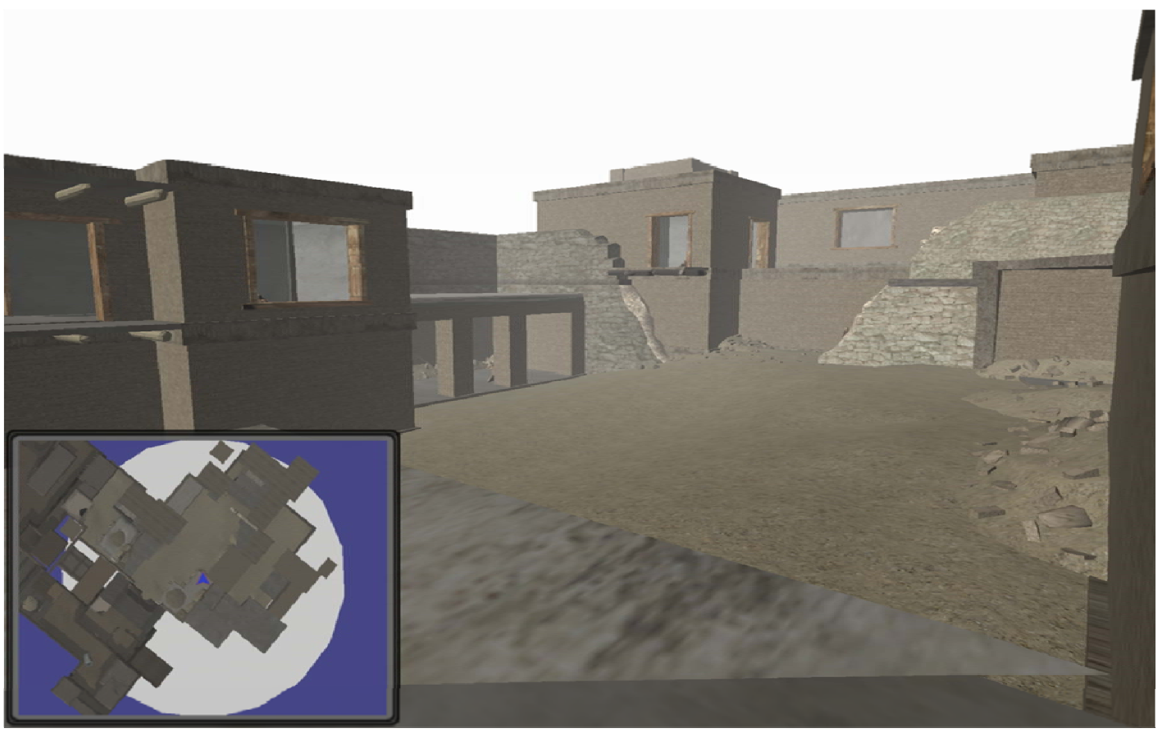
Scene 0002.



Scene 0012.

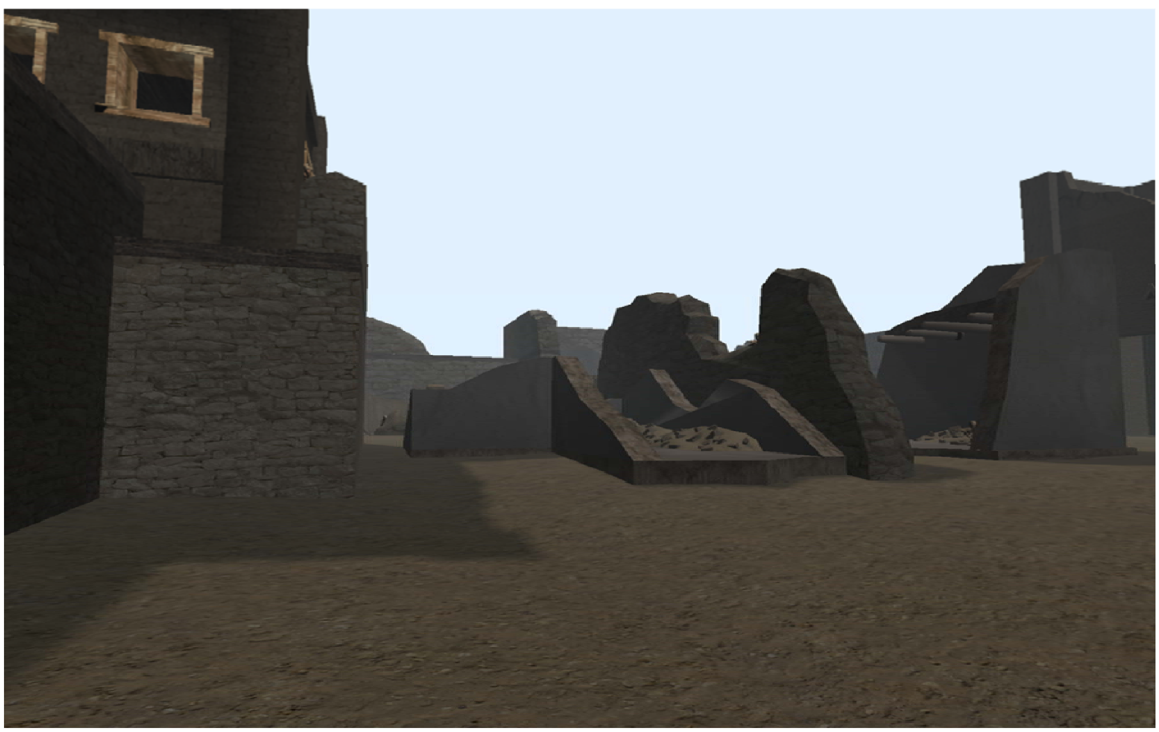


Scene 0019.

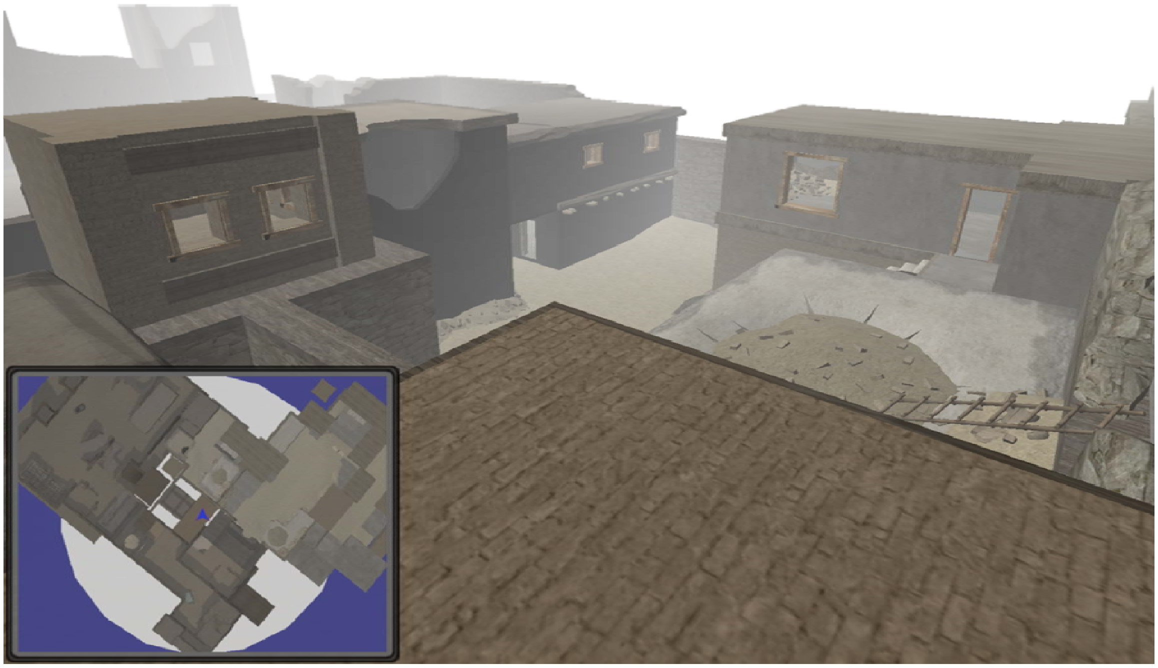


Scene 0020.

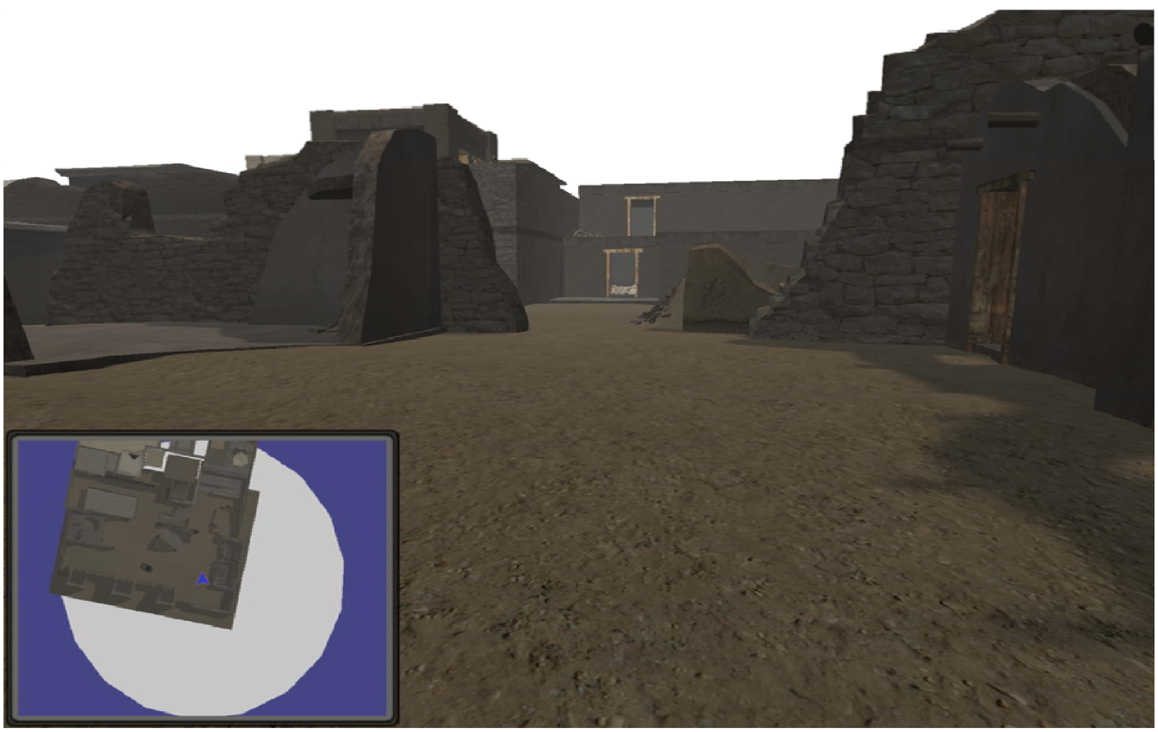
Scene 0021.



Scene 0024.

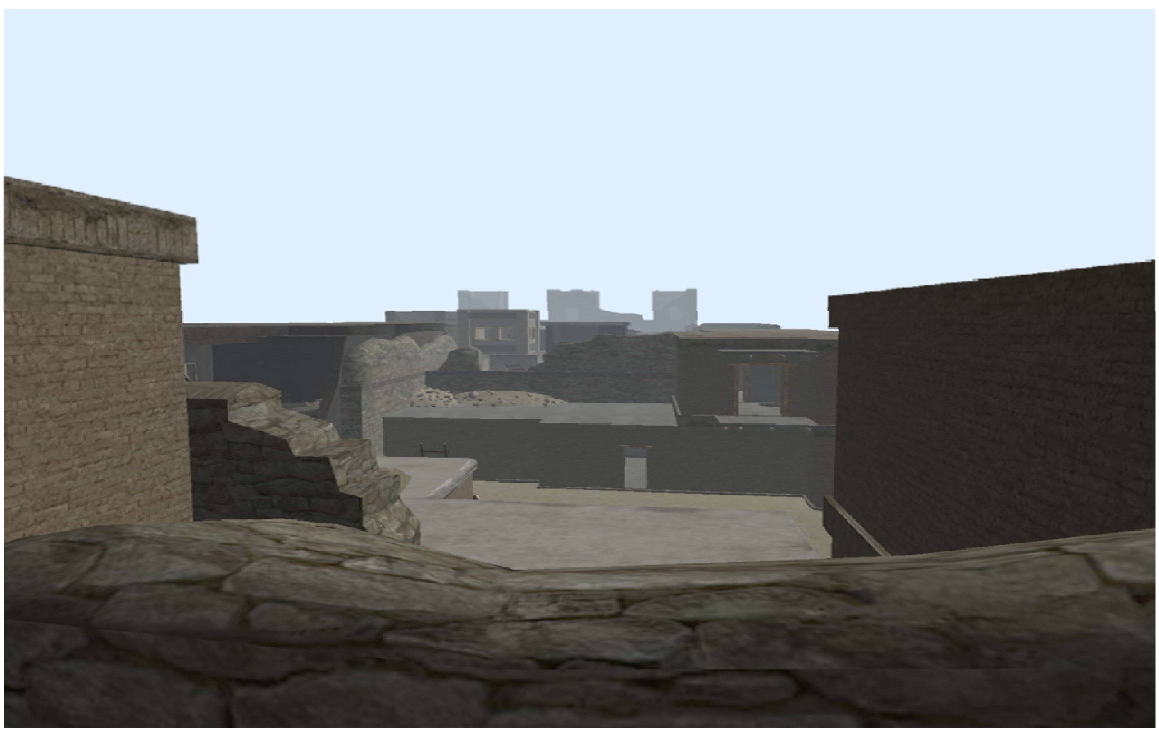


Scene 0027.

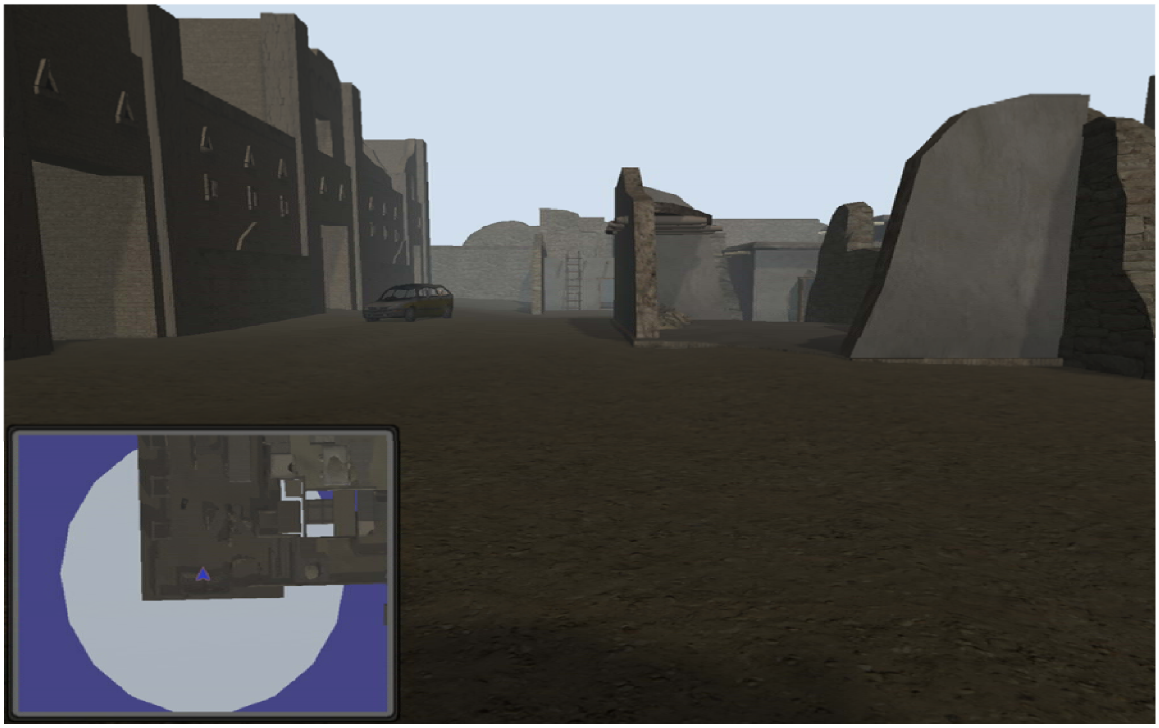


Scene 0033.

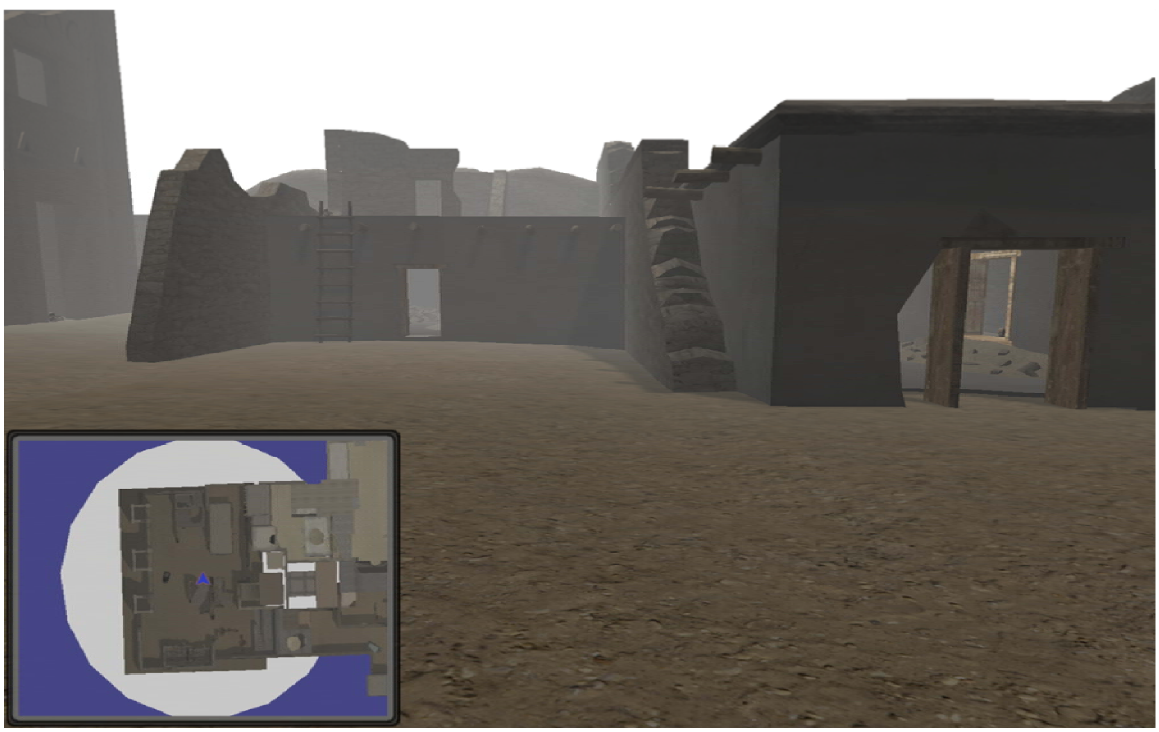
Scene 0035.



Scene 0040.

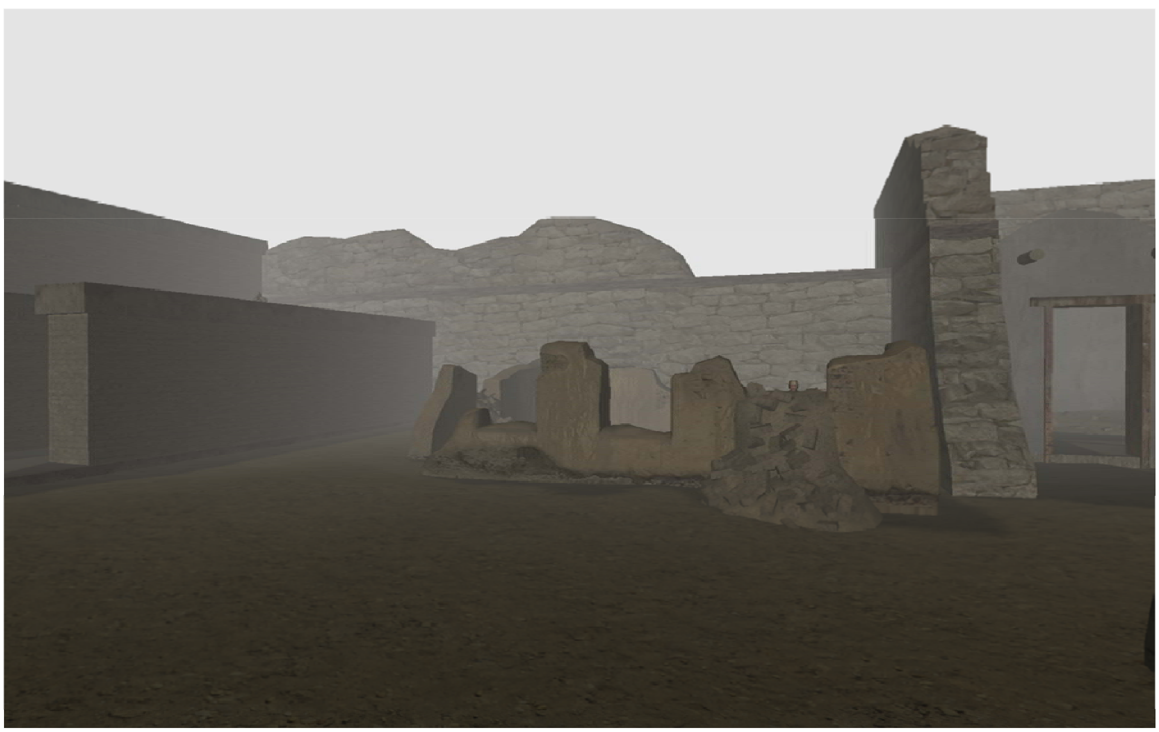


Scene 0041.



Scene 0042.

Scene 0043.



Scene 0044.

Scene 0045.

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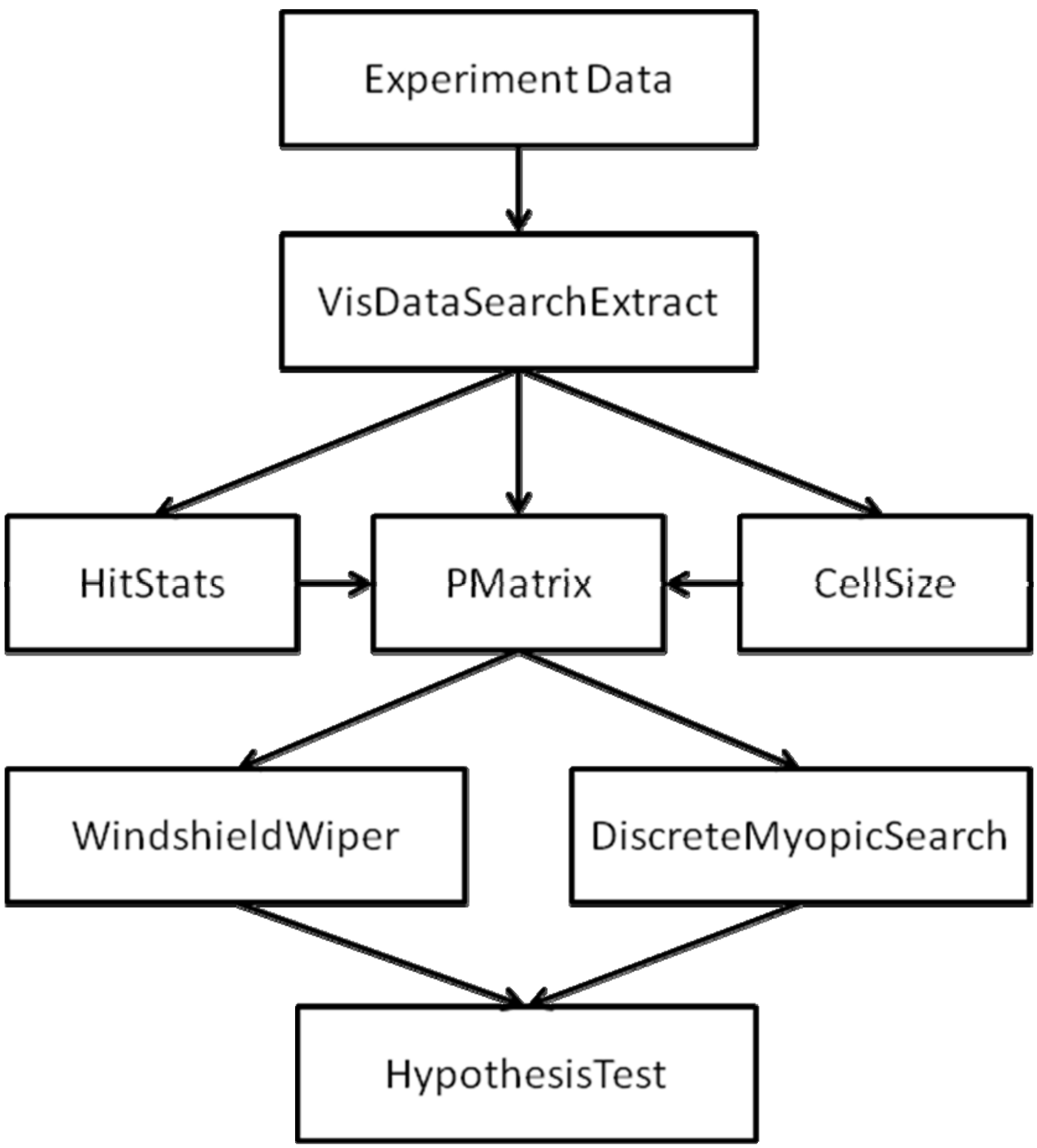
APPENDIX B CODE FLOW CHART AND DESCRIPTION

The flowchart below illustrates the sequence of events to transform the raw experiment data into the results in Chapter 4. The following page provides a brief explanation of each MATLAB script file. This software is a tool which may be used by others in future analysis and may be found at http://faculty.nps.edu/thchung/VisualSearch/scripts/.



`VisDataSearchExtract` uses the pre-processed experiment data to extract detection information and compute fixations for each participant and each scene.

`HitStats` takes participant data input to compute probabilities of detection and conditional probabilities of detection.

`CellSize` takes participant data input to determine the cell size for each image discretization. The cell size is computed based on the average fixation size for all participants for each scene.

`PMatrix` reads in detection probabilities and cell sizes to compute a matrix of probabilities for use in the Discrete Myopic Search model.

`WindshieldWiper` runs the model designed to replicate combat models. The result is a series of matrices, one for each scene, with the order in which each target is detected for each of 1000 iterations.

`DiscreteMyopicSearch` runs the Discrete Myopic Search Model. The result is a series of matrices, one for each scene, with the order in which each target is detected for each of 1000 iterations.

`HypothesisTest` computes the conditional probability of detecting a target in a certain order given a detection for the experiment data and each model. The code then compares the experiment data with the model data by conducting a population proportion hypothesis test for each possible combination of target detection and detection order.

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